

Solar radiance modelling and assimilation

Leonhard Scheck^{1,2}, Bernhard Mayer², Martin Weissmann^{1,2}

- 1) Hans-Ertel-Center for Weather Research, Data Assimilation Branch
- 2) Ludwig-Maximilians-Universität, Munich

Outline

1. Motivation
2. Synthetic satellite images for solar channels
Fast 1D RT, 3D effects, cloud overlap
3. Applications
data assimilation, model evaluation

5 JUNE 2016

N O R T H
S E A

Brussels



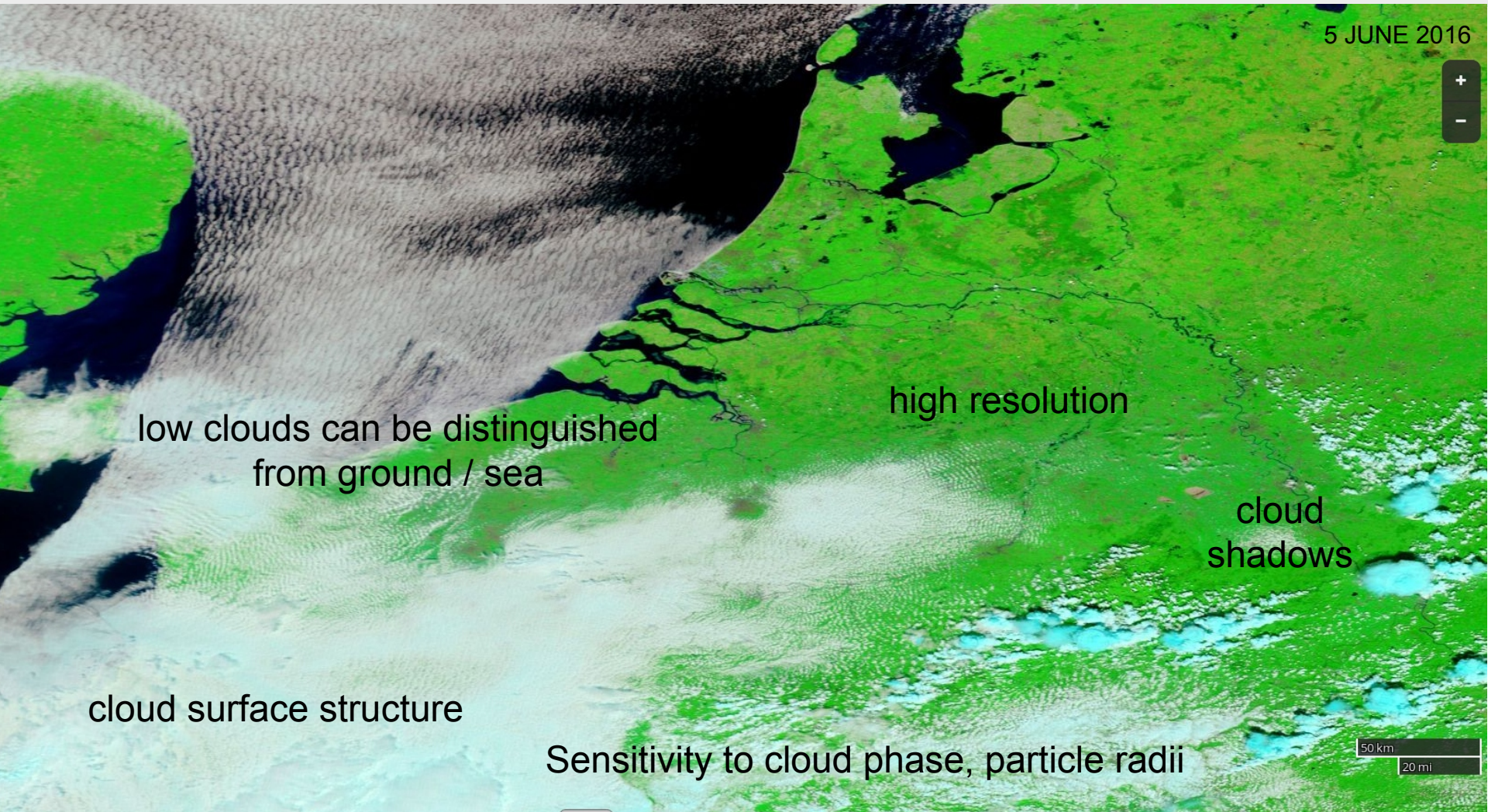
50 km
20 mi

images from NASA WorldView

MODIS 11µm thermal (window) channel, 1km resolution



5 JUNE 2016

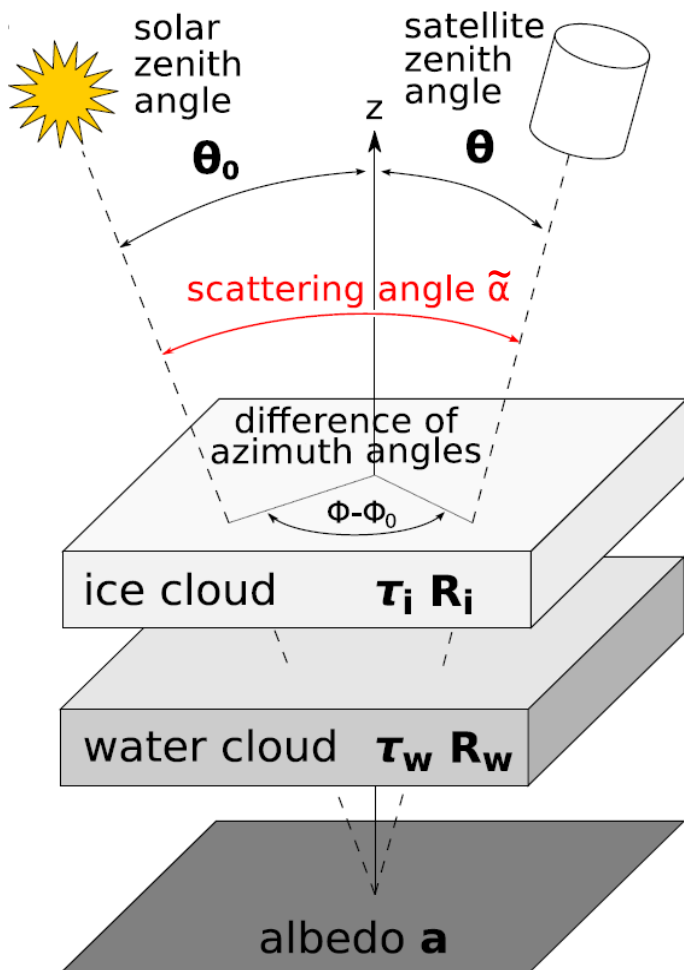


images from NASA WorldView

MODIS $0.6\mu\text{m}$ / $0.8\mu\text{m}$ / $1.6\mu\text{m}$ solar channels, 250m / 250m / 500m resolution

Strategy for fast radiative transfer method MFASIS

Method for Fast
Satellite Image
Synthesis



Simplifications

- Simplified Equation:

3D RT \rightarrow 1D RT (tilted independent columns)

Computational effort for a SEVIRI image of Germany:

CPU-days (3D Monte Carlo) \rightarrow CPU-hours (1D DISORT)

- Simplified vertical structure:

Cloud water and ice can be separated to form two homogeneous clouds at fixed heights without changing reflectance significantly

\rightarrow only 4 parameters (optical depth, particle size)
+ 3 angles, albedo \rightarrow **8 parameters per column**

Reduction of computational effort

Compute **reflectance look-up table (LUT)** with discrete ordinate method (DISORT) for all parameter combinations

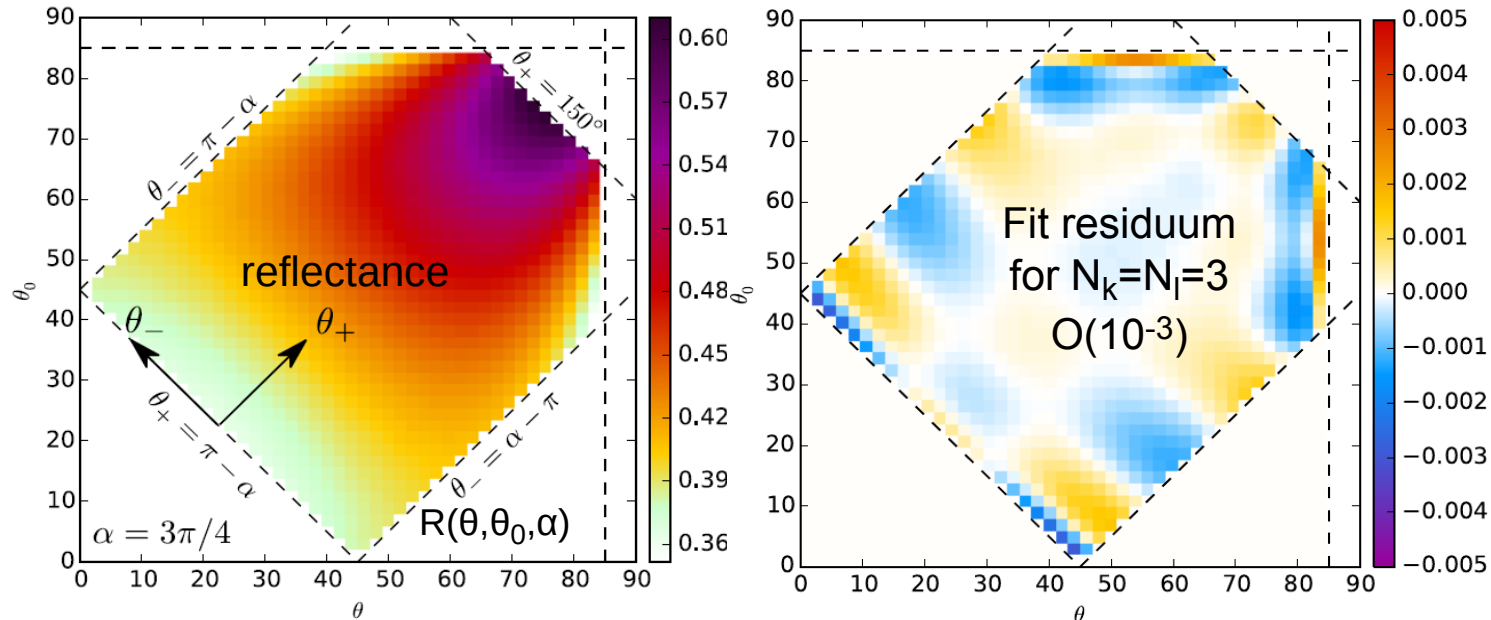
\rightarrow effort for looking up reflectances: CPU-minutes

Problem: Table is huge! O(10GB) \rightarrow not suitable for online operator, slow interpolation \rightarrow **compress table to 20MB** using truncated Fourier series \rightarrow CPU-seconds

Look-up table compression in MFASIS

- **Problem:** $R(\theta, \theta_0, \Phi - \Phi_0)$ contains a lot of rainbow-related small-scale features
- **Solution:** Consider $R(\theta, \theta_0, \alpha)$ instead : smooth function for constant scattering angle α
 → approximate by 2D Fourier series, obtain Fourier coefficients by fit to DISORT results

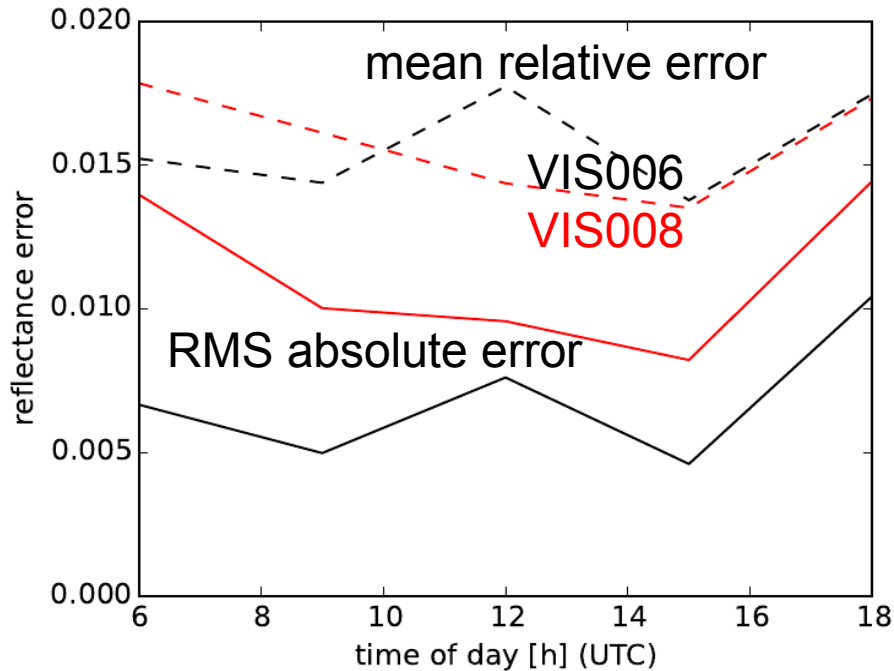
Fit function:
$$R(\theta_+, \theta_-) = \sum_{k=0}^{N_k-1} \sum_{l=0}^{N_l-1} \left[C_{k,l} \cos(k\theta_+) + S_{k,l} \sin((k+1)\theta_+) \right] \cos(l\theta_-)$$
 where $\theta_+ = \theta + \theta_0$
 $\theta_- = \theta - \theta_0$



We need to store only 18 coefficients C_{kl} , S_{kl} instead of $O(1000)$ reflectance values (for each combination of the remaining 6 parameters) → **compression by a factor of $\sim O(100)$**

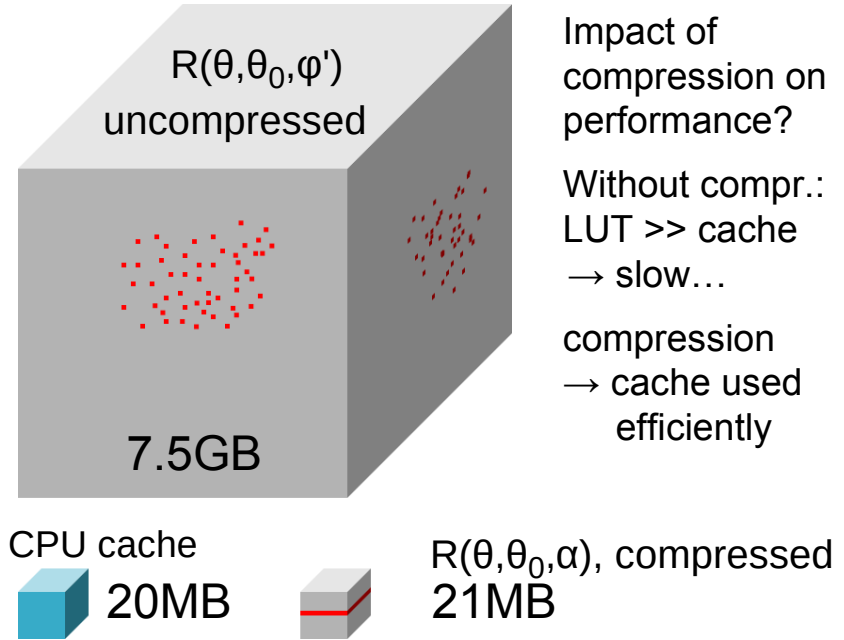
Accuracy and computational effort

Error of MFASIS (8 parameters/pixel) with respect to DISORT (full profiles available)
(model data: COSMO-DE fcsts for 10-28 June 2012)



Relative error < SEVIRI calibration error (~4%) for almost all pixels

Computational effort per column:
DISORT (16 streams): 2.3×10^{-2} CPUsec
MFASIS (21MB table): 2.5×10^{-6} CPUsec
(on Xeon E5-2650, for 51 level COSMO data)



NWP-SAF → MFASIS has been included in RTTOV 12.2 by DWD + MetOffice

MFASIS for aerosols?

Fourier compression:

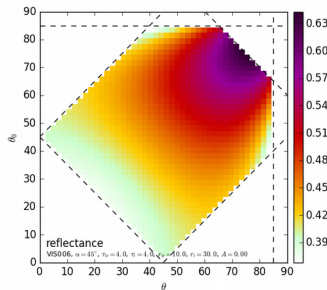
No obvious problem, same number of Fourier coefficients should be ok for aerosols...

Main problems:

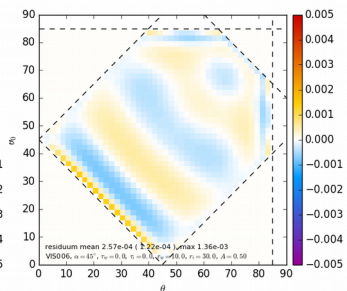
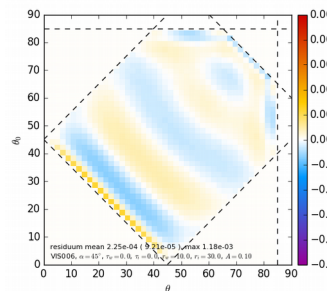
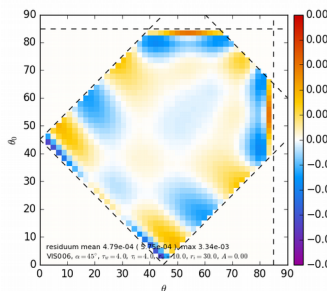
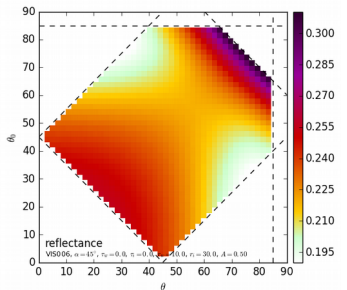
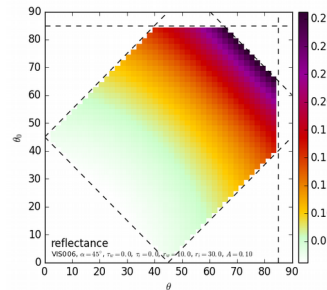
- Large number of LUT dims.: Many species ($O(10)$), in case of COSMO-ART also effective radii
- Vertical profiles matter: Aerosol A can overlap aerosol B and vice versa

Reflectance(SZA,VZA) for const. scatt. angle + fit residuum

Cloud example from MFASIS paper

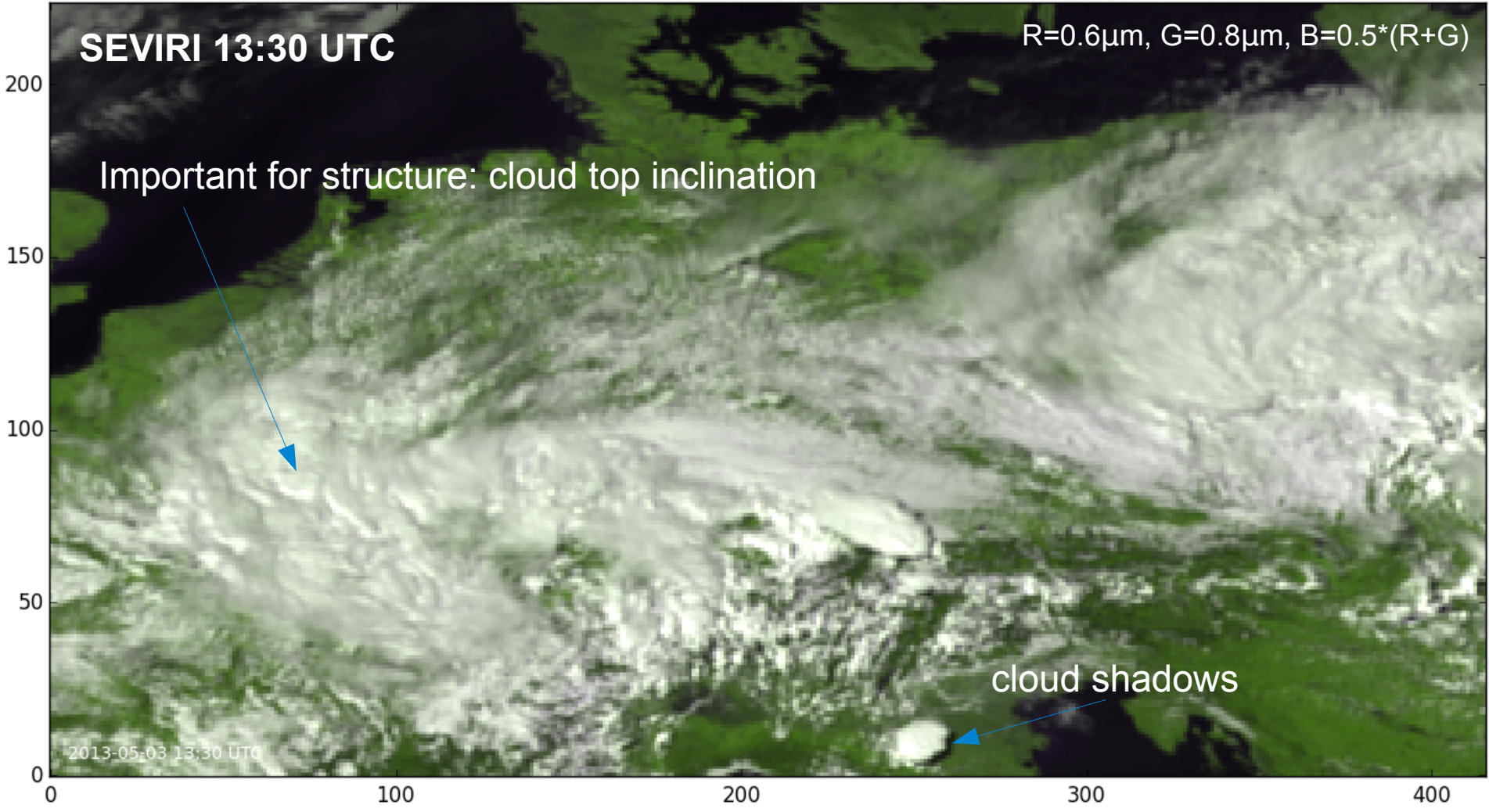


OPAC aerosol mixture "urban", AOD=1
Albedo=0.1 Albedo=0.5

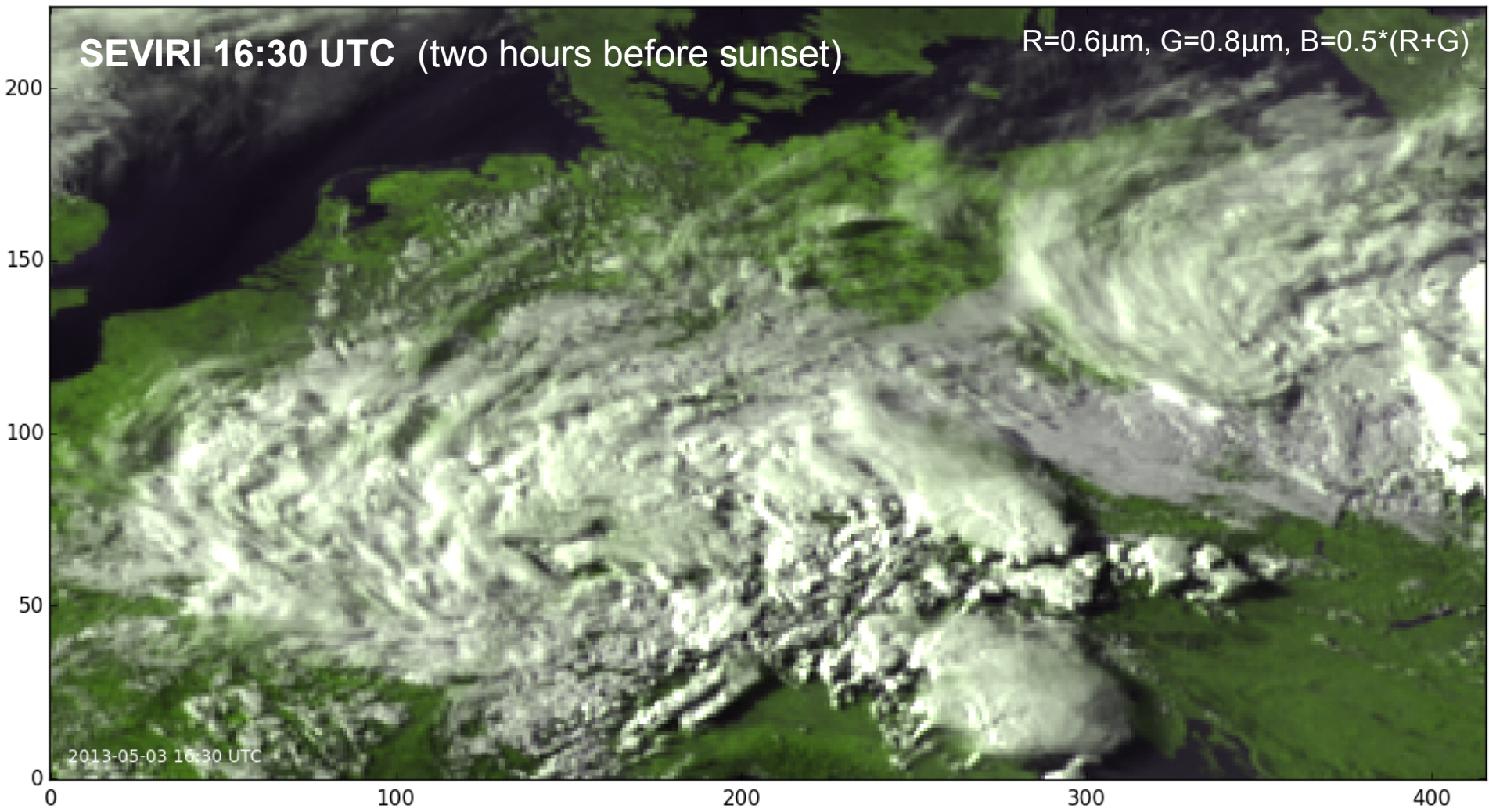


Plan: Investigate how the vertical structure can be simplified without causing too large reflectance errors, test if it is sufficient to consider only the N (=2,3?) most important aerosol species in each column...

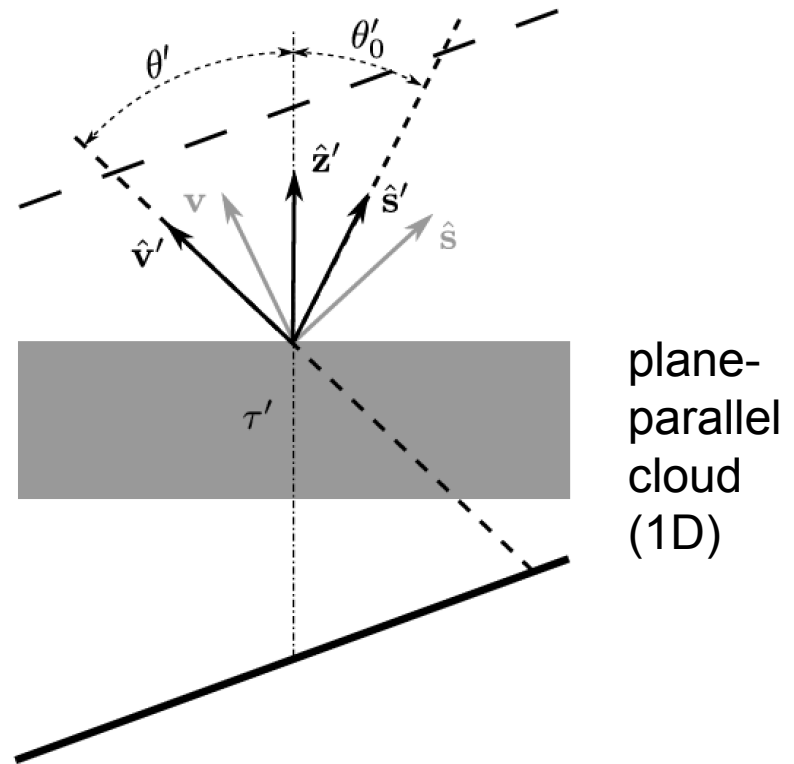
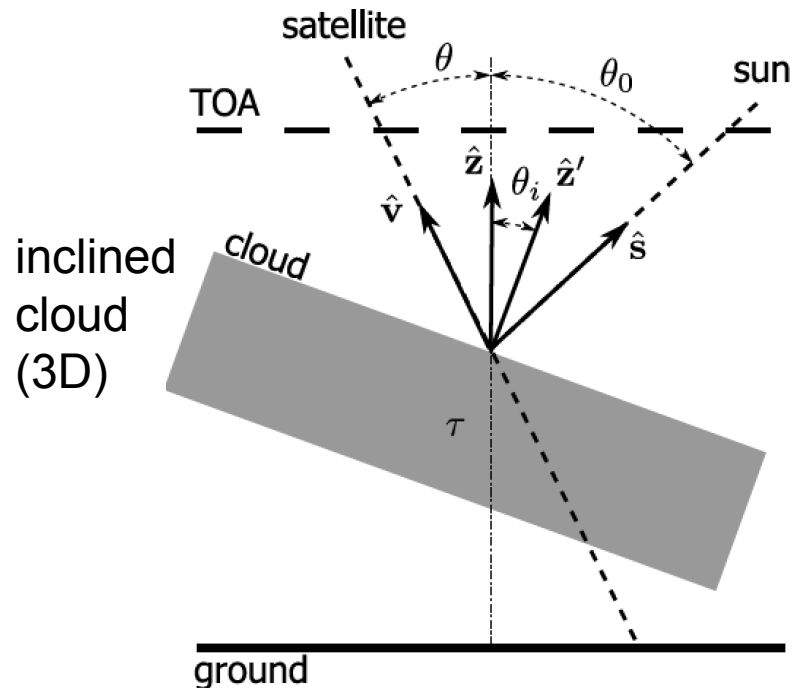
3D effects not accounted for in 1D radiative transfer



3D effects not accounted for in 1D radiative transfer



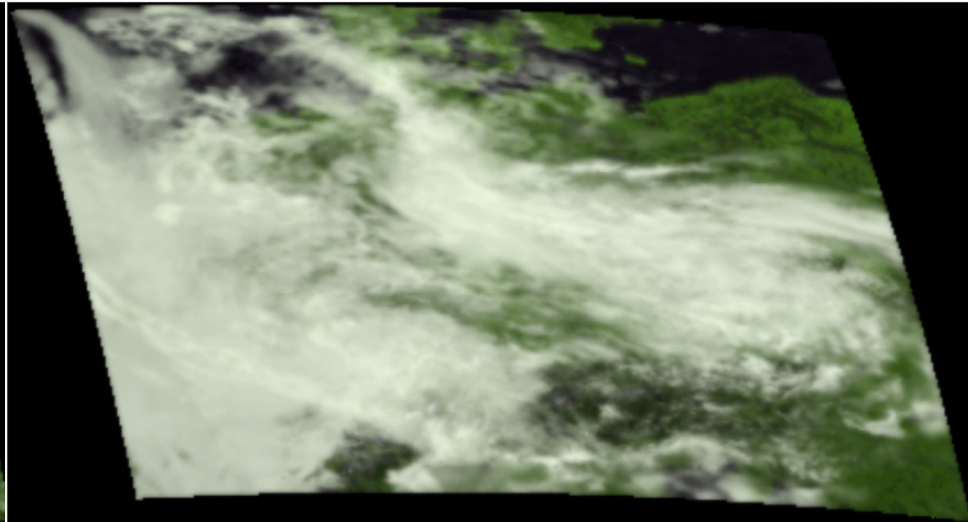
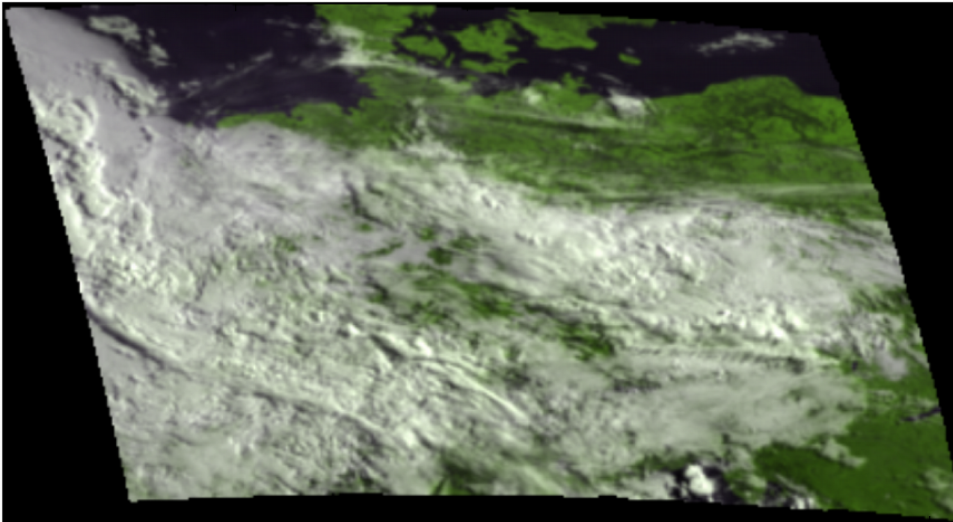
Accounting for 3D RT effects: Cloud top inclination



$$R_T(\theta, \theta_0, \alpha, A, \tau, \theta_i) = R(\theta', \theta'_0, \alpha, A', \tau \cos \theta_i) \frac{\cos \theta'_0}{\cos \theta_0}$$

Rotated frame of reference with ground-parallel cloud → nearly a 1D problem (inclined ground is taken into account by using a modified surface albedo)
→ Solve modified 1D problem, transform back to non-rotated frame.

Cloud top inclination



SEVIRI 0.6 μ +0.8 μ , 3 June 2016, 6UTC

3h COSMO fcst **without 3D correction**

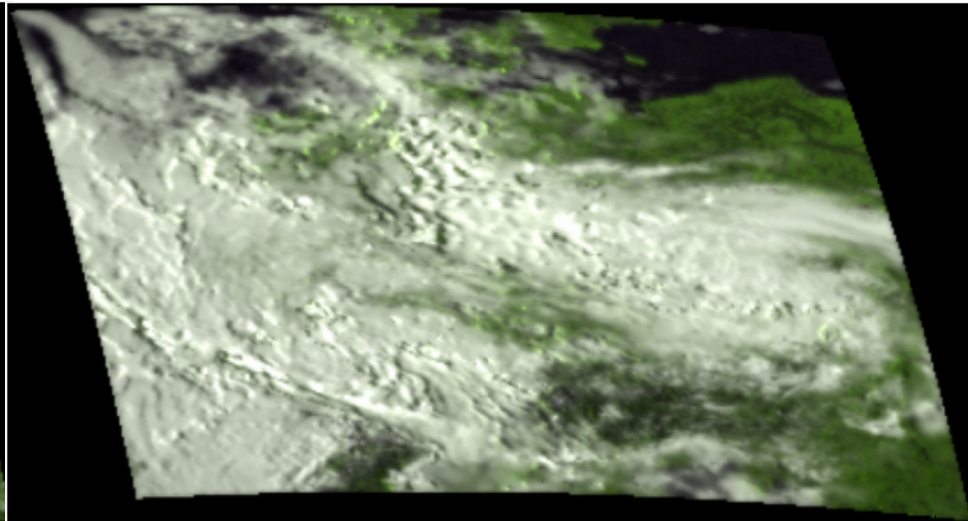
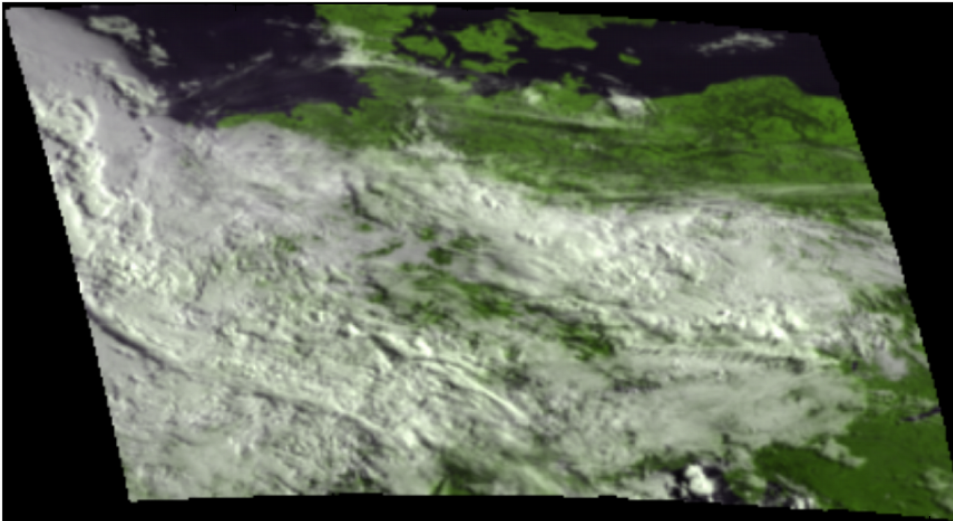
Cloud top definition : optical depth 1 surface
(detect $\tau=1$ in all columns, fit plane to column and 8 neighbour columns)

Cloud top inclination correction → **Increased information content**

Much more cloud structure is visible, in particular for larger SZAs

For instance, one can distinguish convective from stratiform clouds

Cloud top inclination



SEVIRI 0.6 μ +0.8 μ , 3 June 2016, 6UTC

3h COSMO fcst **with 3D correction**

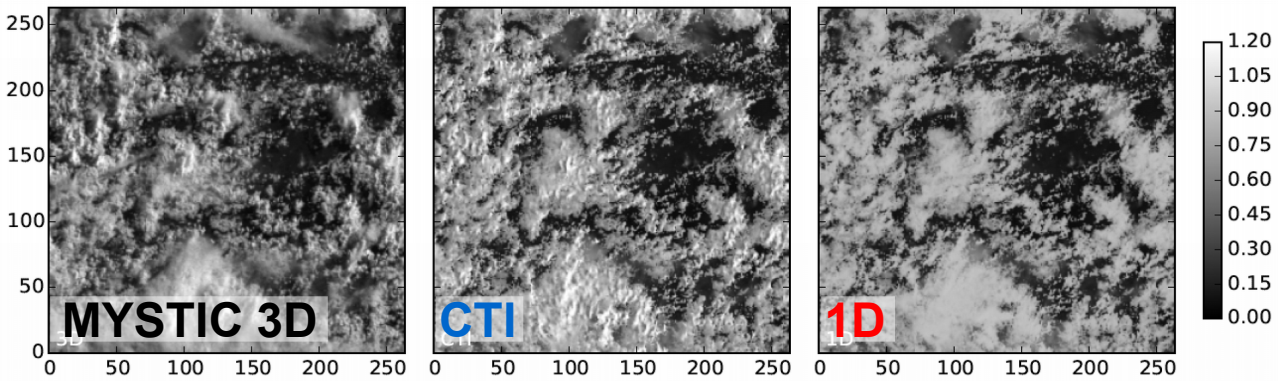
Cloud top definition : optical depth 1 surface
(detect $\tau=1$ in all columns, fit plane to column and 8 neighbour columns)

Cloud top inclination correction → **Increased information content**

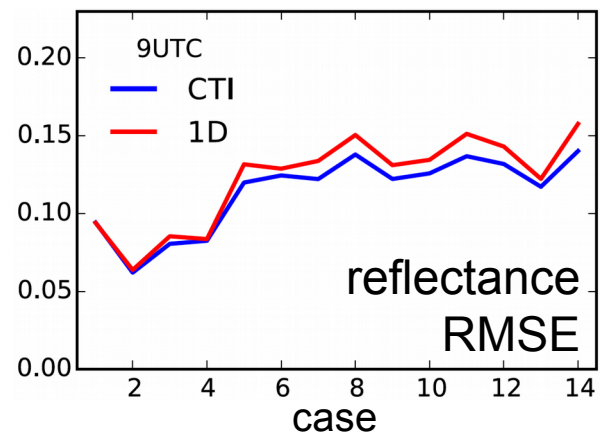
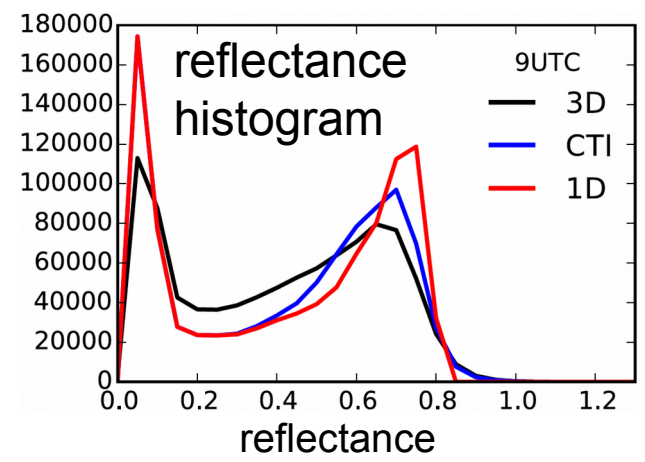
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Comparison with 3D Monte Carlo RT calculations



Clean comparison (only RT errors, no model errors) based on high-res. ICON runs from the HD(CP)² project:



- RMSE is reduced
- Histogram shape is improved
- Derived empirical function to scale down 3D correction for thinner clouds

Other 3D effects are still missing (e.g. shadows, flux through cloud sides)...

Cloud overlap schemes for synthetic satellite images

RT must take assumptions about **overlap of subgrid clouds** into account.

So far: Schemes for 1D RT in vertical columns, $> O(10\text{km})$ grid, deterministic

Here: Columns tilted towards satellite, $O(\text{km})$ grid, ensemble DA (no adjoint req.)

→ **Questions: How important is...**

...the uncertainty related to the unknown subgrid cloud distribution for DA?

Do we need a stochastic scheme?

...this inconsistency: Overlap assumptions are valid for **vertical direction**, whereas 1D RT is performed in **columns tilted towards** the satellite

...the **cloud size distribution?** (What are we assuming at the moment?)

→ experiments with different schemes

Not addressed: “What is the best overlap assumption?”

We consider only maximum-random (as used in COSMO):

*Clouds in adjacent layers overlap maximally,
clouds separated by empty layers overlap randomly.*

Implementation 1: RTTOV „streams“ approach

(Matricardi 2005)

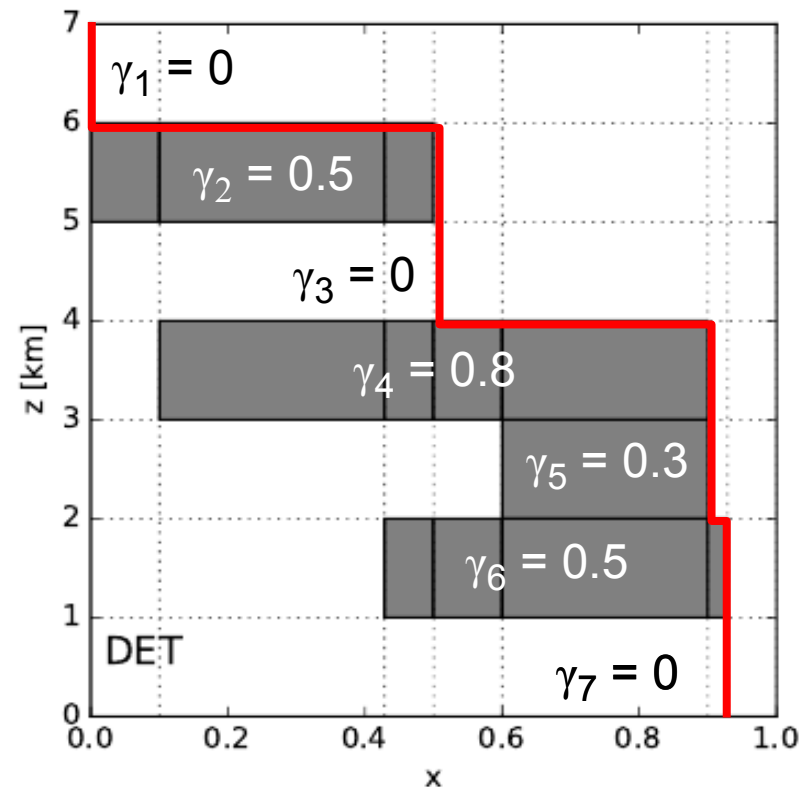
- For each layer: compute total cloud fraction γ_{tot} , „right-align“ single cloud

$$1 - \gamma_{\text{tot}}^{\text{randmax}}(n) = (1 - \gamma_1) \prod_{k=2, \dots, n} \frac{1 - \max(\gamma_k, \gamma_{k-1})}{1 - \gamma_{k-1}}$$

where γ_k = cloud fraction in layer k

(can be derived under the assumption that there are no horizontal correlations)

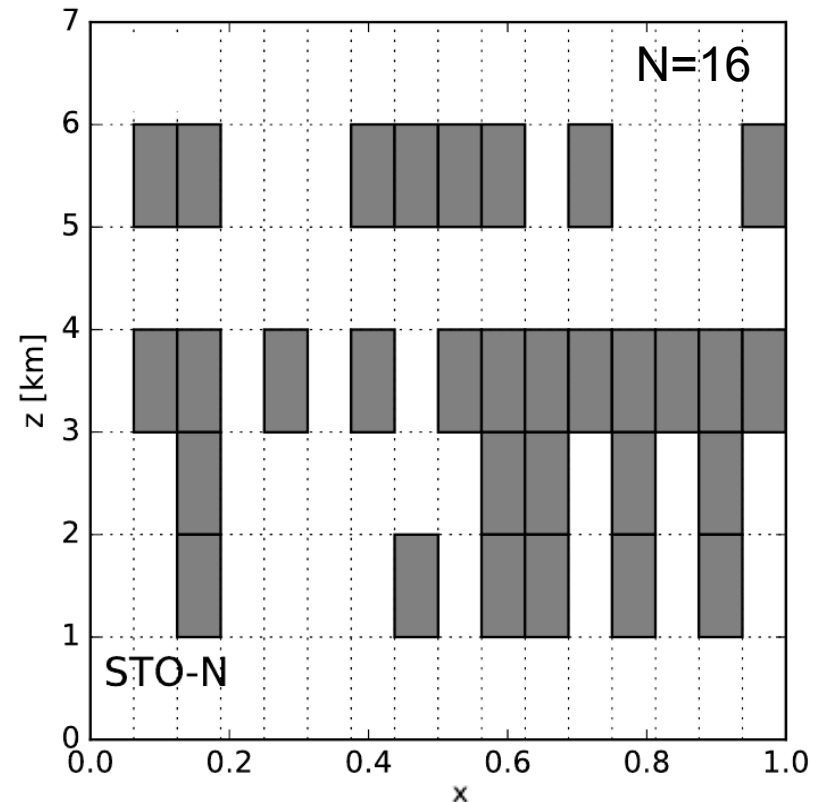
- Subcolumn boundaries are created where needed → **variable number of subcolumns** („streams“), up to $2N_z$



Implementation 2: Stochastic cloud generator

Räisänen (2004), Marquart & Mayer (2001)

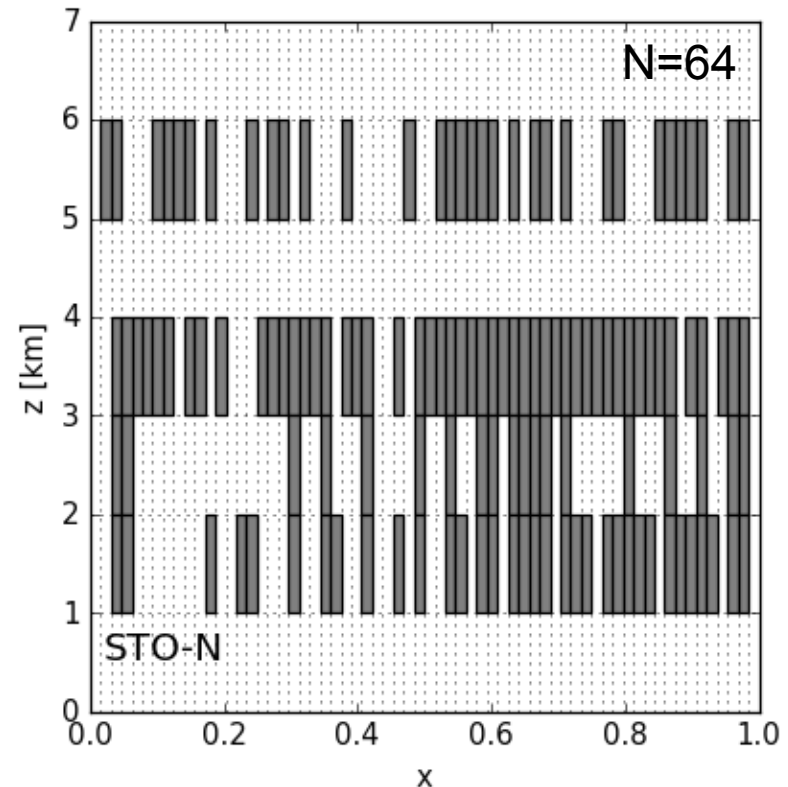
- **Fixed number of subcolumns N**
- Subcolumns are **independently** filled with clouds according to stochastic rules
→ correct expectation values γ , γ_{tot}
- Clouds wider than 1 subcolumn form only by chance → we assume **clouds are as small as possible**.
- Convergence: Average over $n \rightarrow \infty$ realizations converges to the same value as every single realization for $N \rightarrow \infty$
→ **spread is only related to discretization error**, vanishes for $N \rightarrow \infty$
→ Physical spread requires finite cloud size



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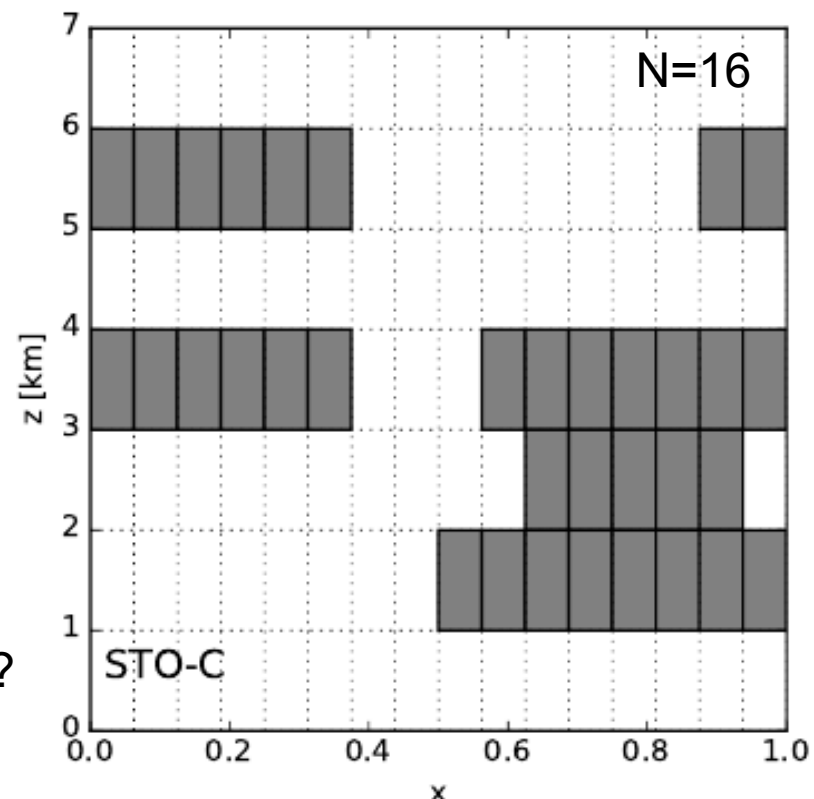
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Implementation 3: Stochastic continuous clouds

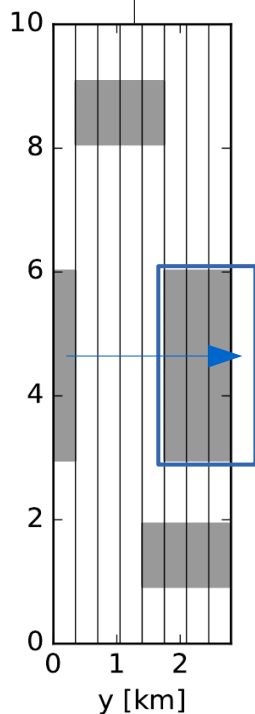
- Exactly one continuous cloud per layer (periodic boundaries)
→ **clouds as large as possible**
- **Fixed number N of subcolumns**
(cloud fraction discretization error $< 1/N$)
- Cloud positions are limited by rand.-max. rules, but otherwise random
- Average total cloud cover for many realization converges to a value that is in general different from the equation (correlation between subcolumns)
- Spread does not vanish for $N \rightarrow \infty$
but **converges to a finite value**

Upper limit for spread that would result from a more realistic cloud size distribution?

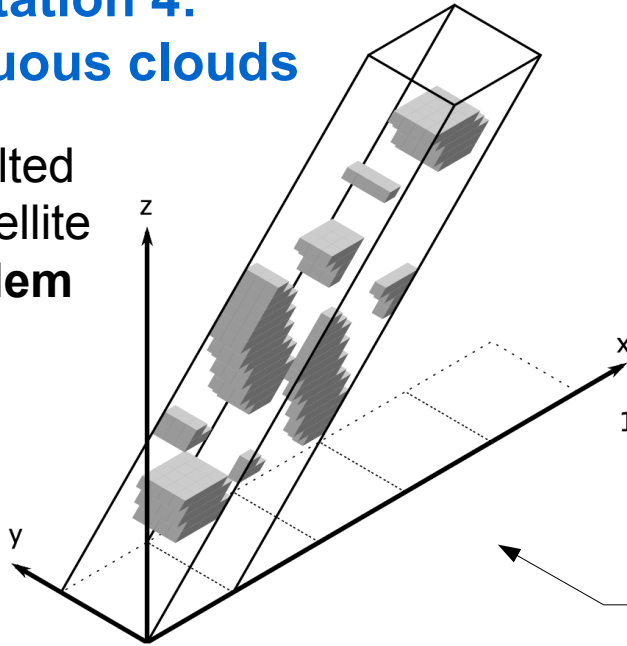


Implementation 4: 3D continuous clouds

Column is tilted
towards satellite
→ **3D problem**

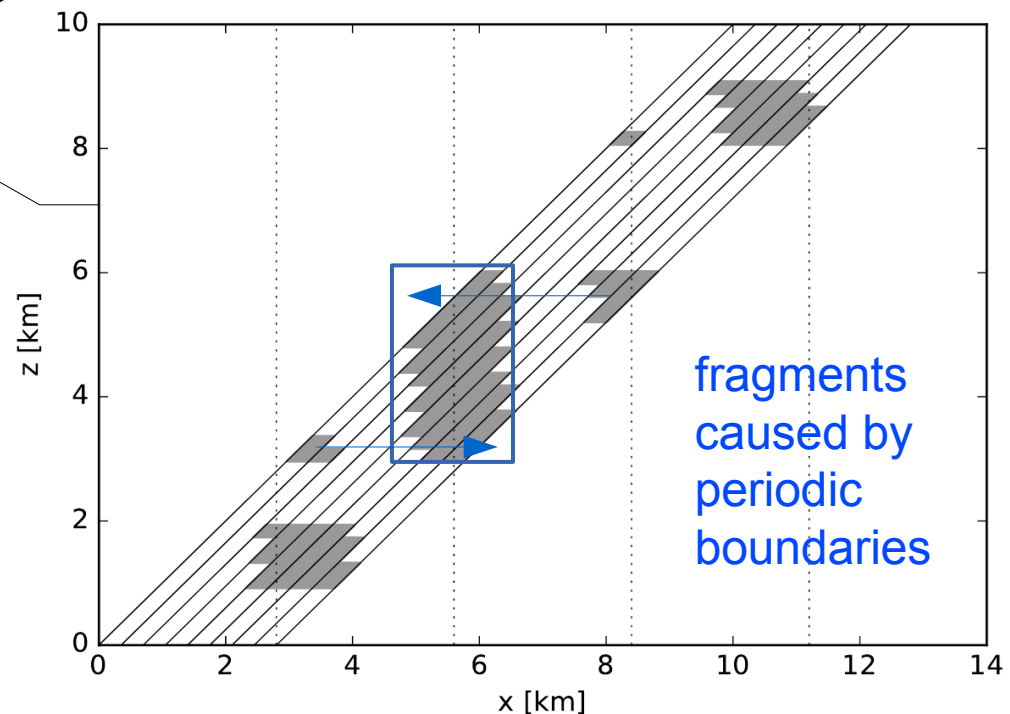


→ **Increased total
cloud cover**
(also cloud sides
contribute)



Example: 3 clouds with constant cloud fraction 0.25 spanning several layers, bundle of 8×8 subcolumns

Maximum overlap holds for the vertical direction, not along the tilted column
→ compensate by shift in x -direction in each layer → nearly vertical clouds



Results for June 2016

based on operational 3h COSMO-DE fcsts

- All 2D maximum-random implementations lead to similar results for the mean values

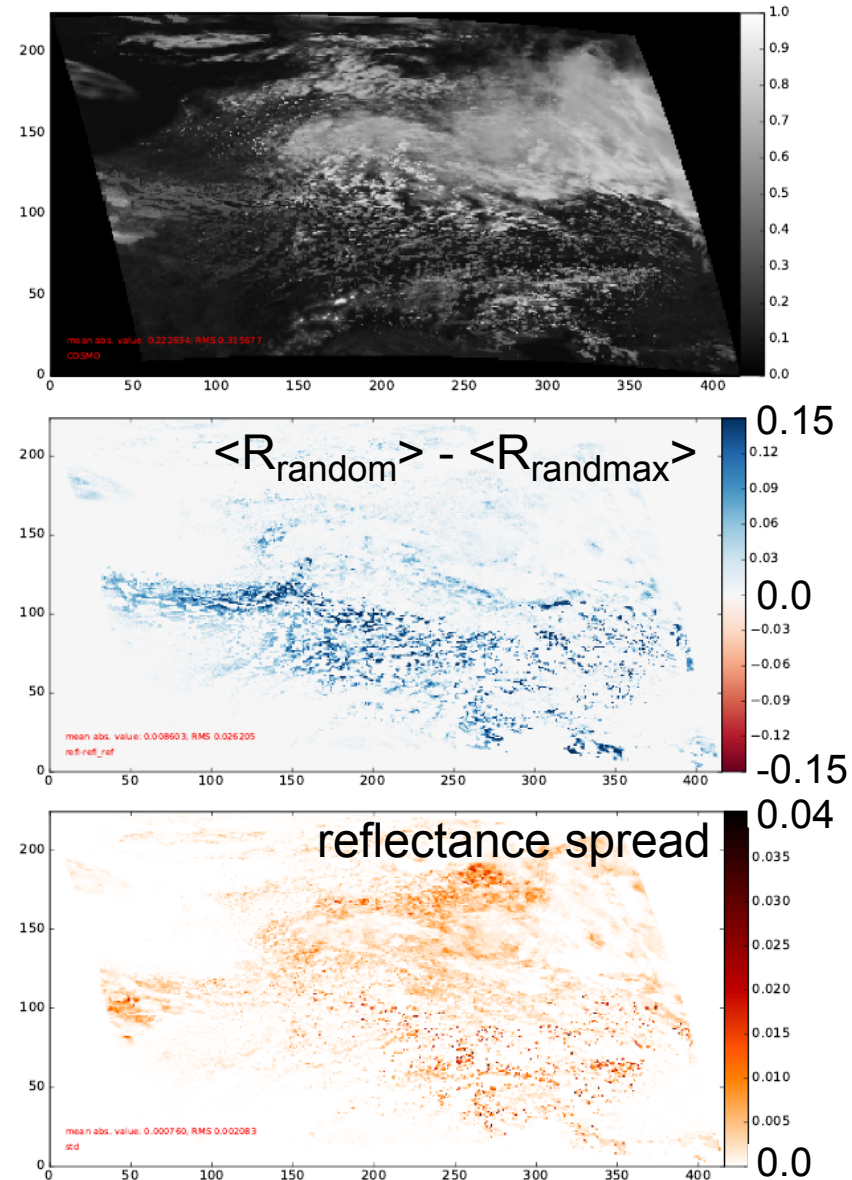
- **Spread** obtained for continuous clouds is small, exceeds 0.01 in only 12% of pixels, max. spread is 0.05

→ **probably not relevant for DA**

- **Most consistent implementation:** 3D maximum-random results are closer to 2D random than to 2D max.-rand. (local reflectance differences up to 0.15)

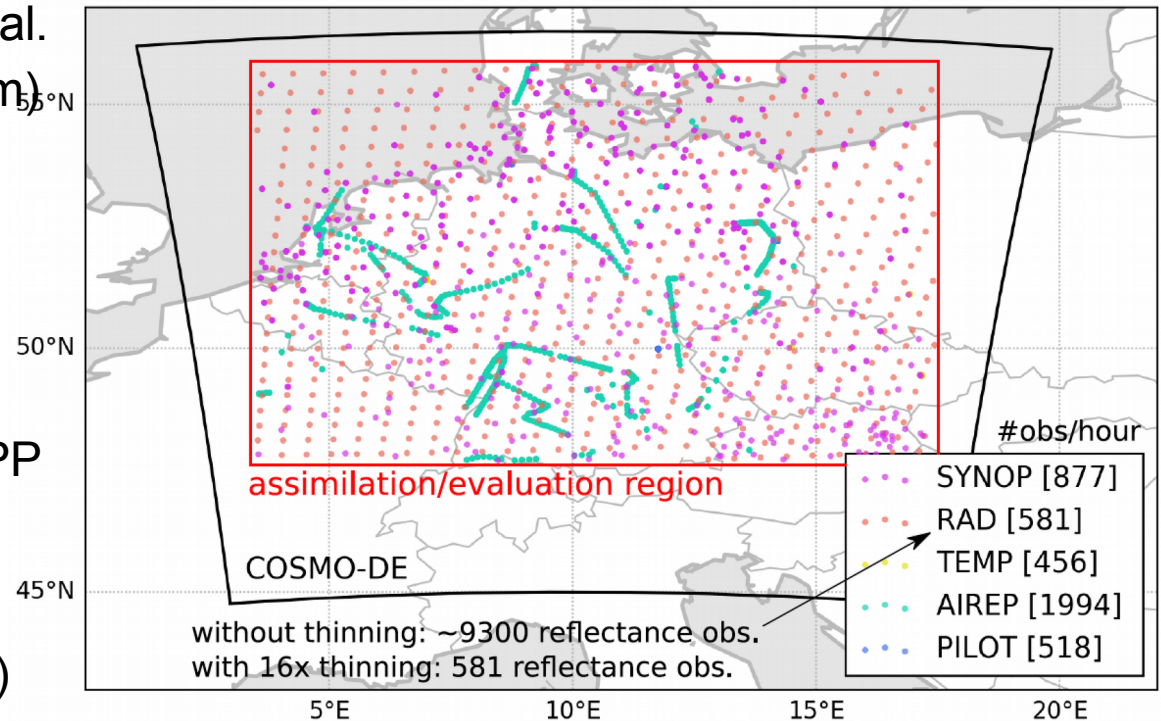
→ Taking tilted columns into account is of similar importance as the choice of the overlap assumption.

- Missing in all implementations: **Shadows...** (Not a problem for thermal channels)



LETKF (Local Ensemble Transform Kalman Filter) Assimilation experiments

- **Codes:** KENDA (Schraff et al. 2016) + COSMO-DE (2.8km)
- **Case:** 5 June 2016
- **Ensemble:** 40 members
- **Assimilation window:** 1h
- **Covariance inflation:** Additive + multiplicat. + RTPP
- **Conventional obs.:** SYNOP, TEMP, Profiler, AMDAR (no MODE-S, LHN) ~5000 observations/hour
- **Reference runs:** Cycling with conv. obs. from June 4th, 21UTC - June 5th, 18UTC
- **Runs with conventional obs. + 0.6 μ m VIS SEVIRI channel:** Branched from ref. run at 5UTC → first analysis at 6UTC

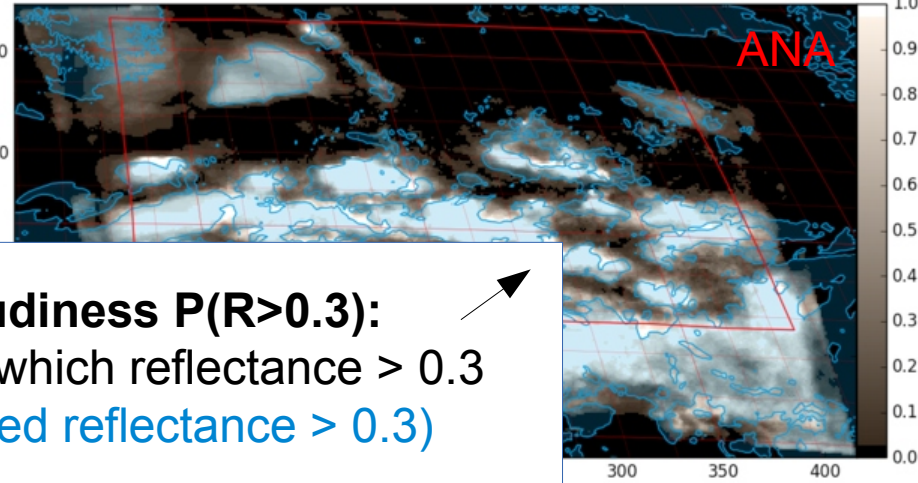
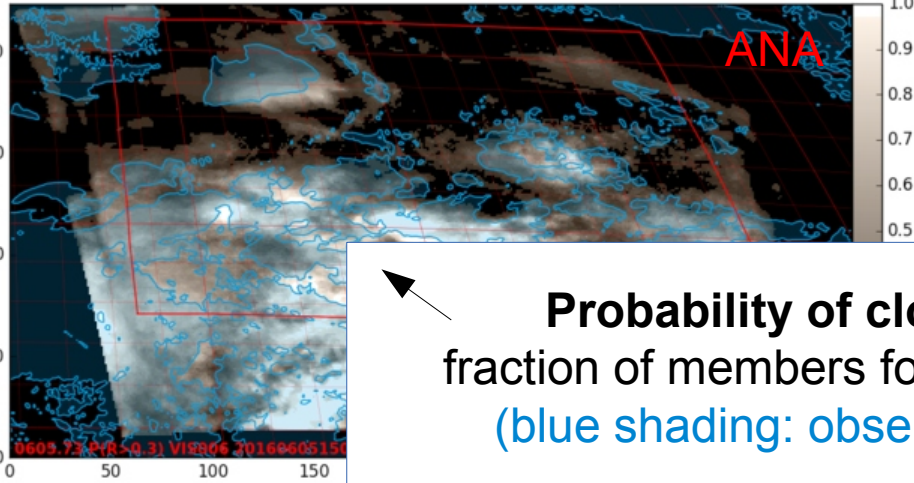


P(R>0.3)

only conventional obs.

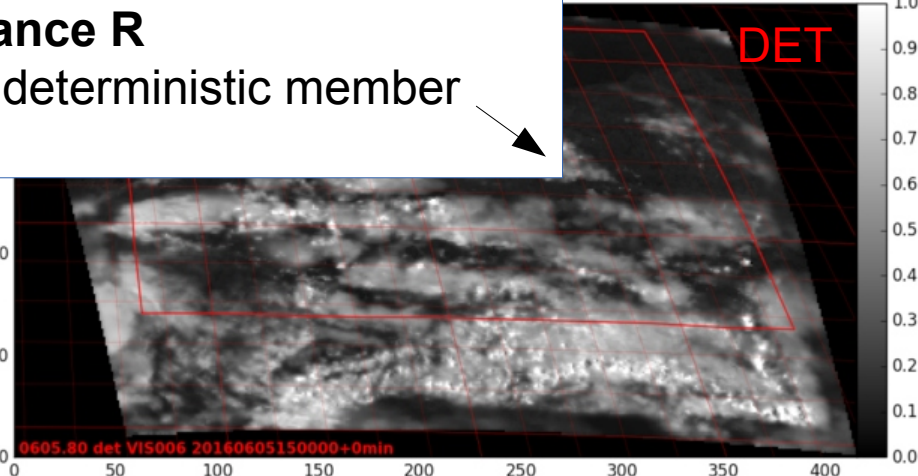
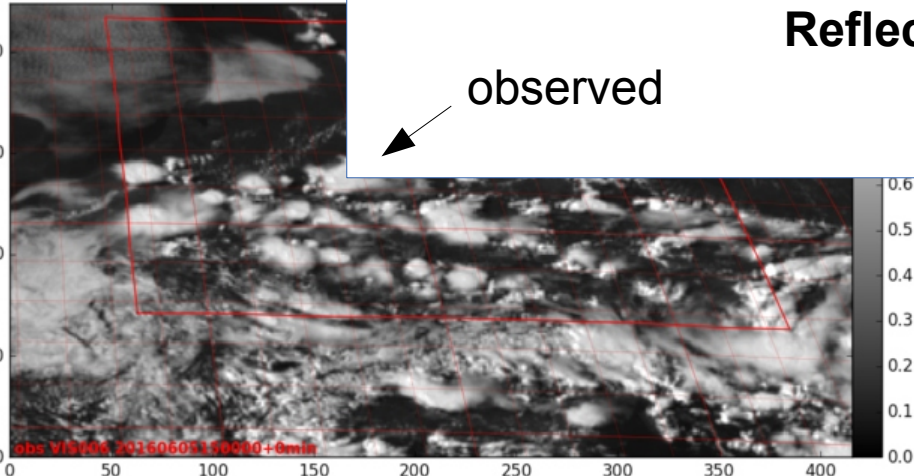
P(R>0.3)

conventional + SEVIRI 0.6mu



Probability of cloudiness P(R>0.3):
fraction of members for which reflectance > 0.3
(blue shading: observed reflectance > 0.3)

Reflectance R
observed deterministic member



R SEVIRI 0.6mu observation

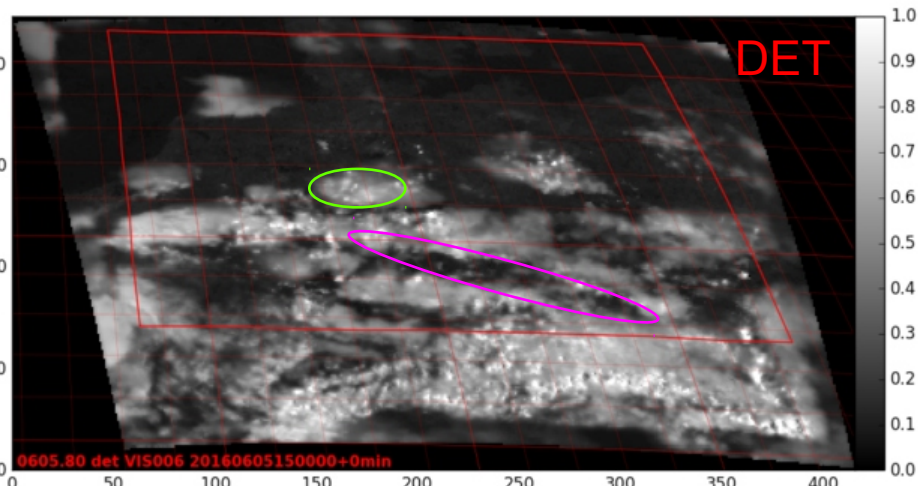
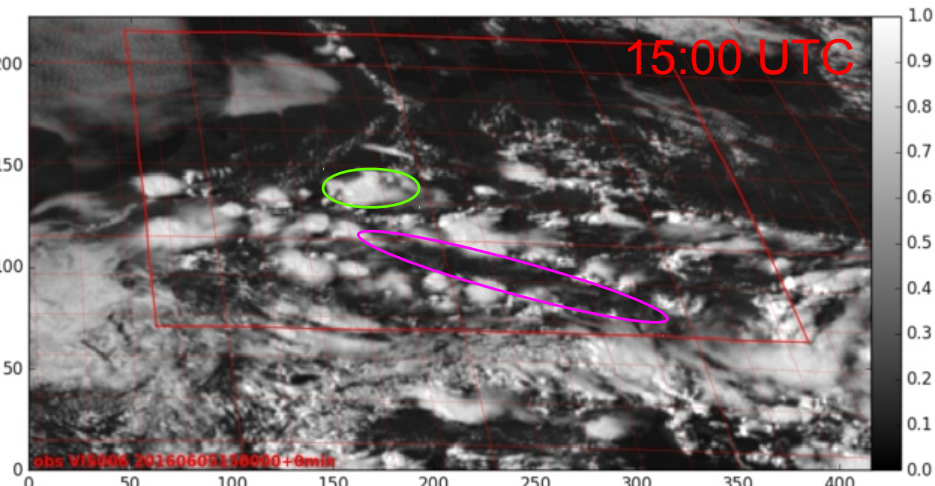
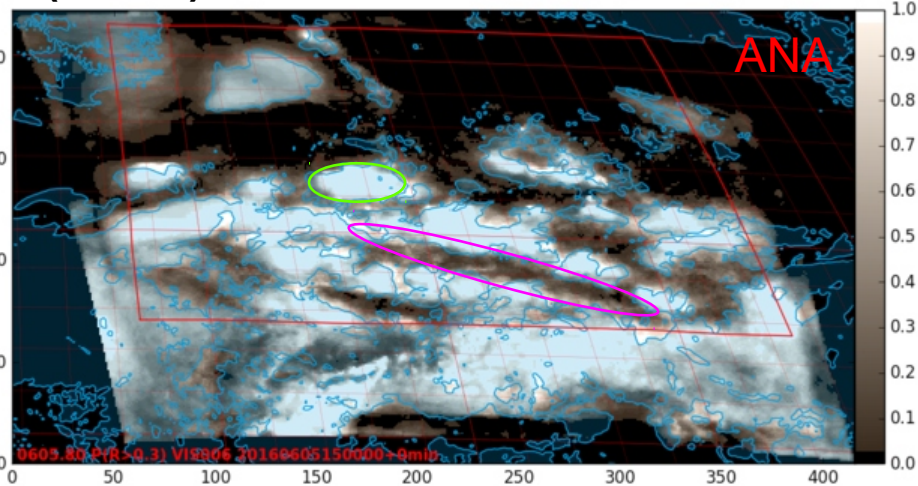
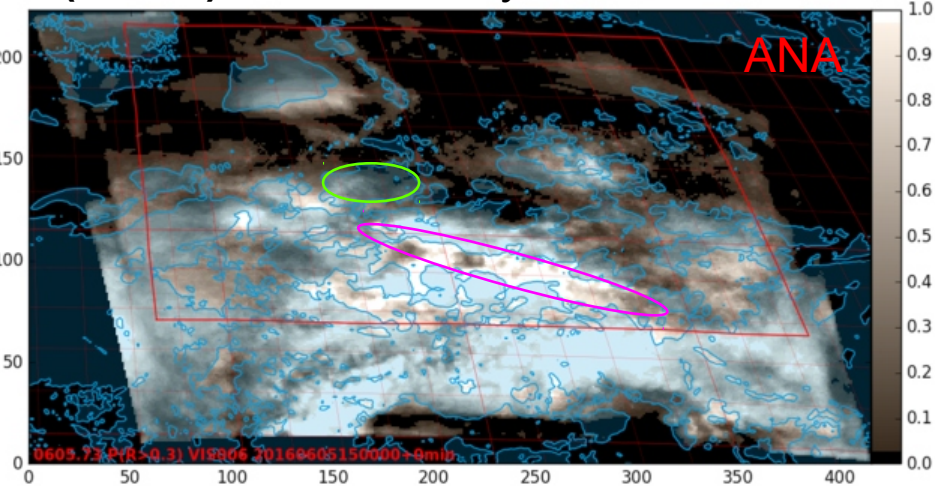
R det. member from conv. + SEVIRI

P(R>0.3)

only conventional obs.

P(R>0.3)

conventional + SEVIRI 0.6mu



R SEVIRI 0.6mu observation

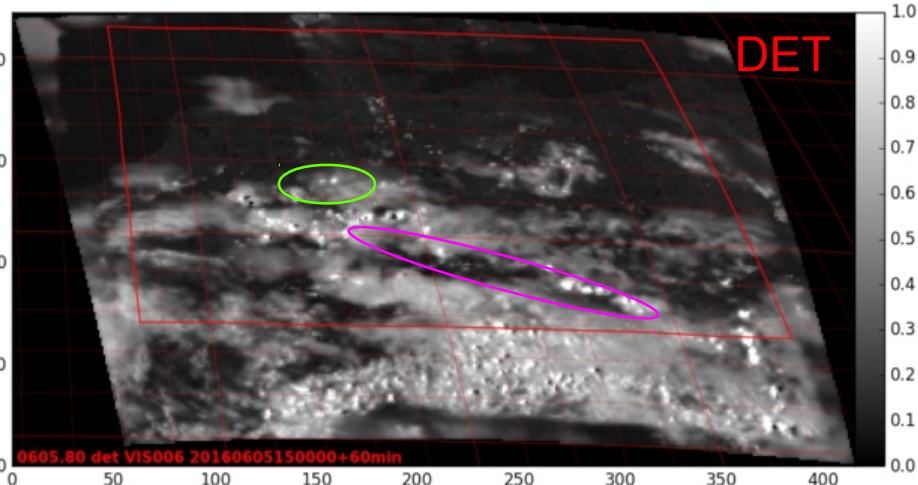
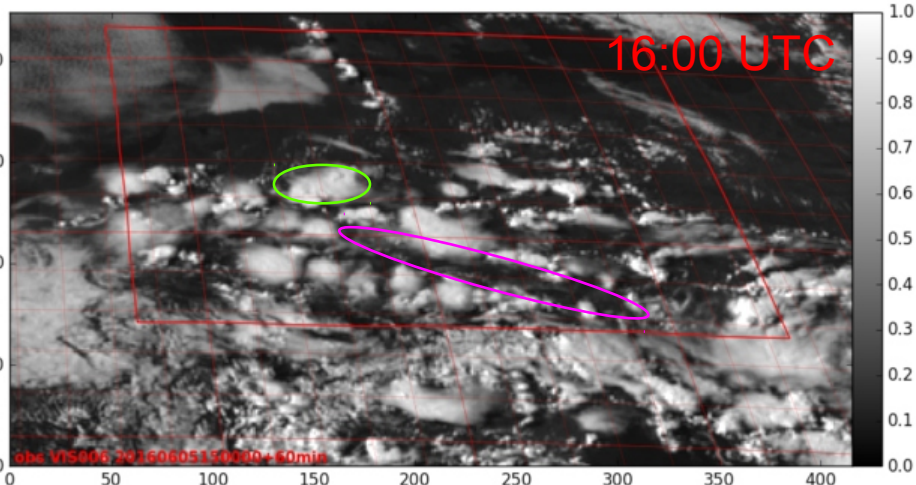
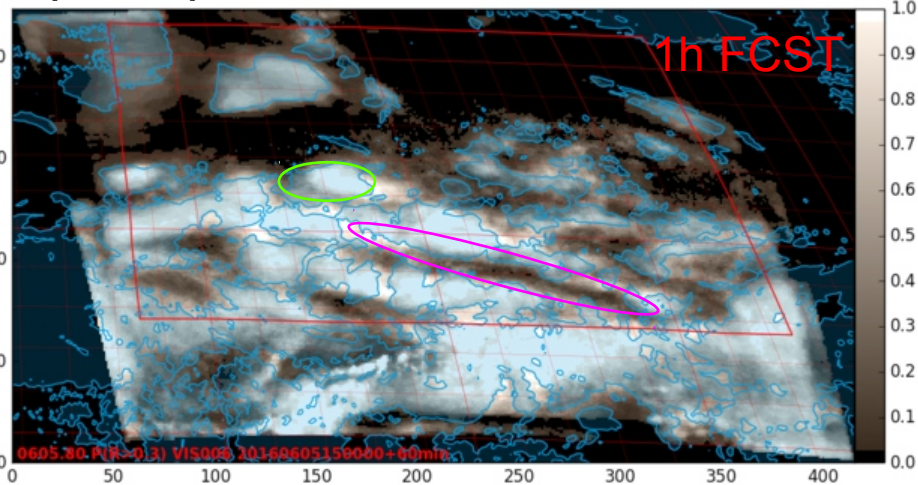
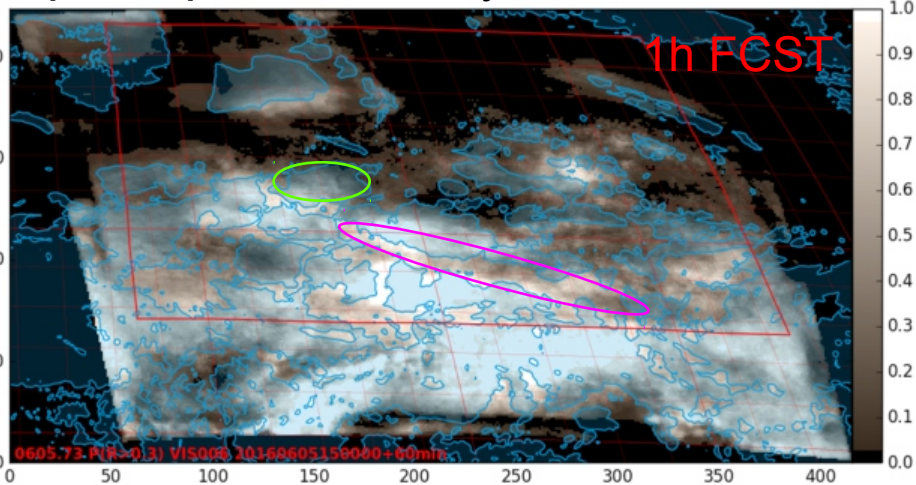
R det. member from conv. + SEVIRI

P(R>0.3)

only conventional obs.

P(R>0.3)

conventional + SEVIRI 0.6mu



R SEVIRI 0.6mu observation

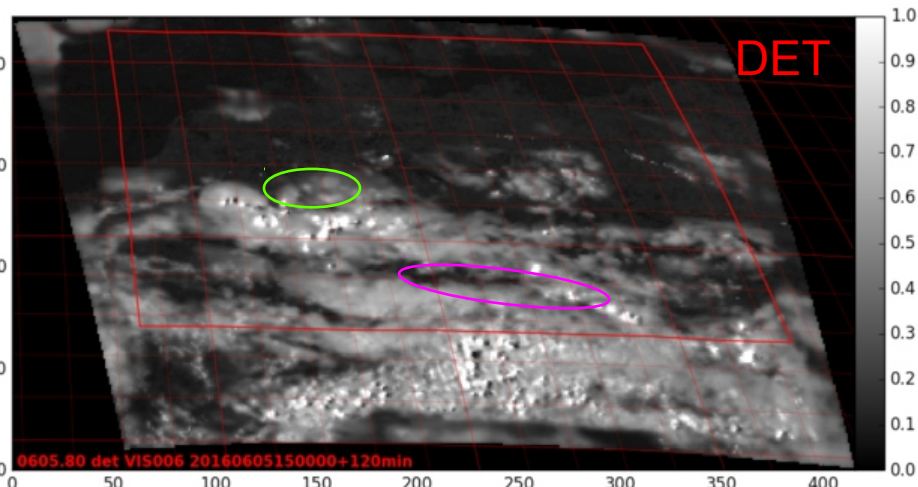
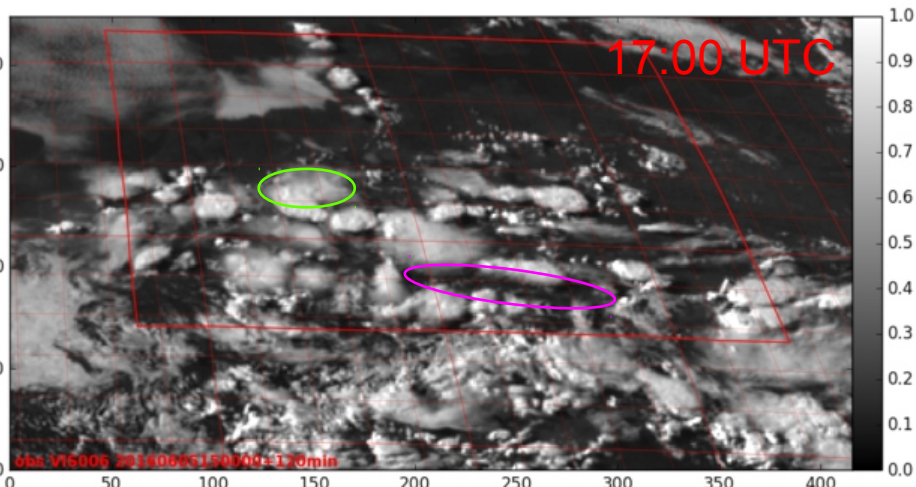
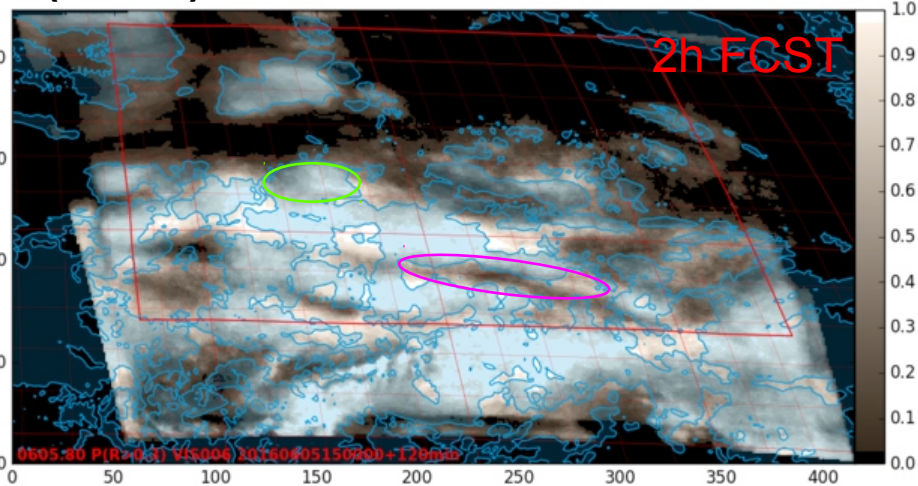
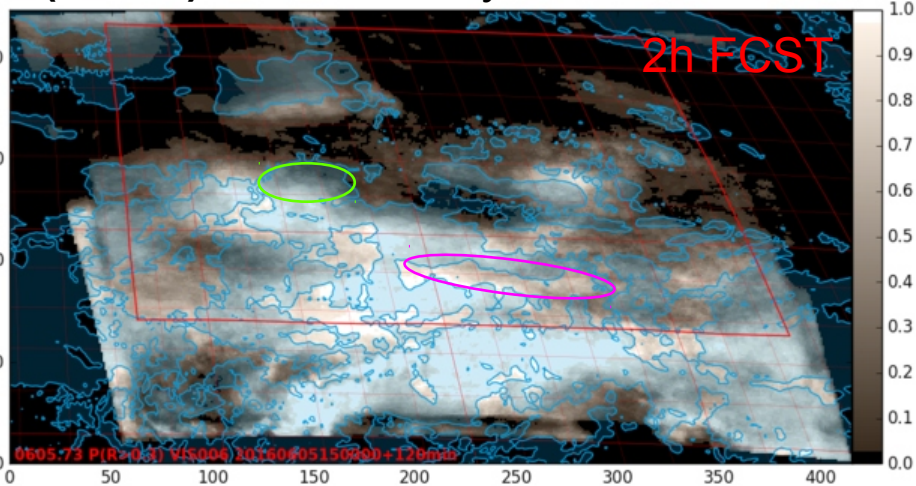
R det. member from conv. + SEVIRI

P(R>0.3)

only conventional obs.

P(R>0.3)

conventional + SEVIRI 0.6mu



R SEVIRI 0.6mu observation

R det. member from conv. + SEVIRI

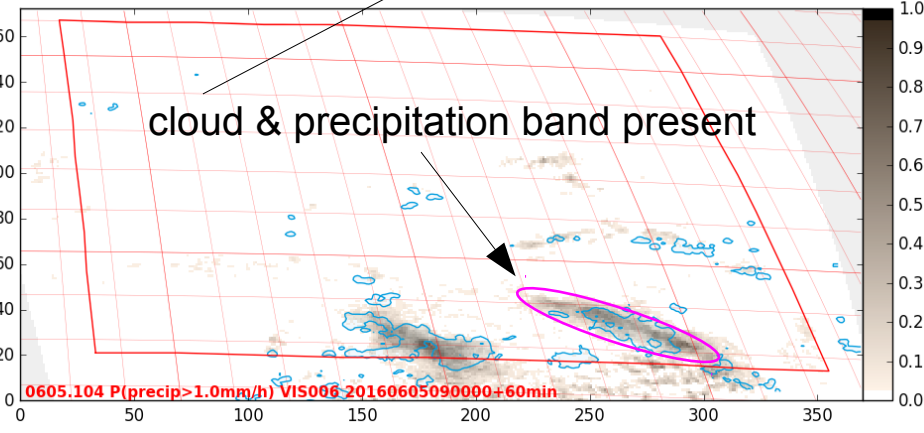
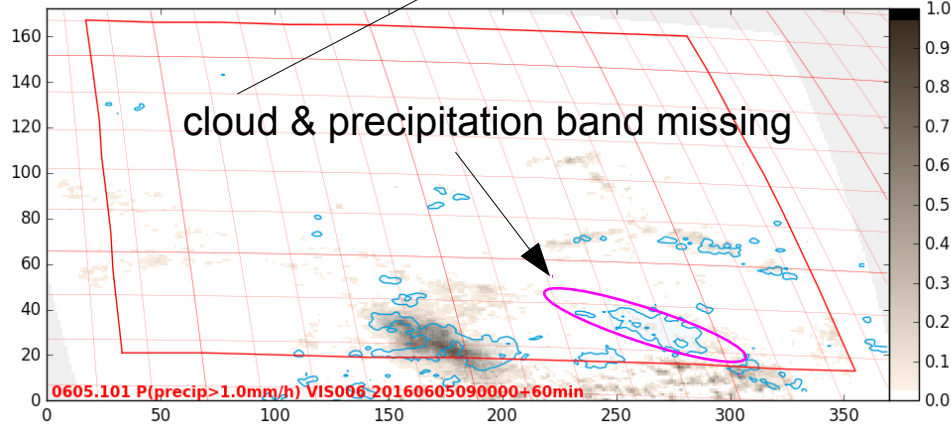
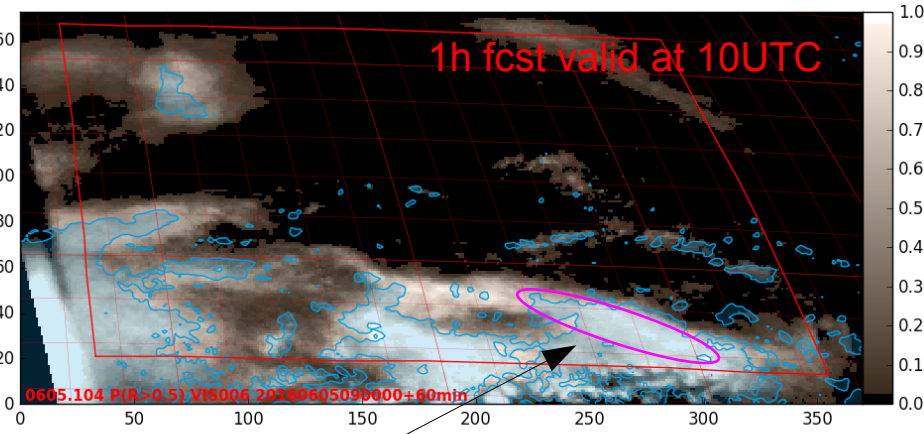
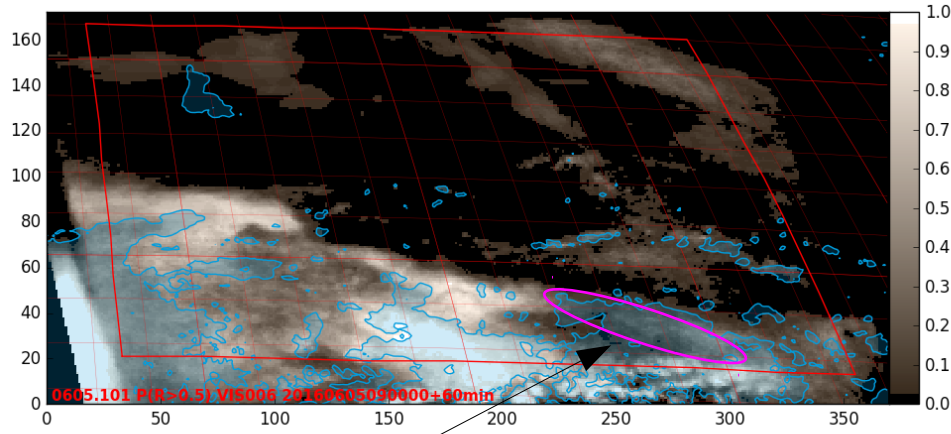
Precipitation forecast improvements

P(R>0.5)

only conventional obs.

P(R>0.5)

conventional + SEVIRI 0.6mu



P(PRECIP>1mm/h)

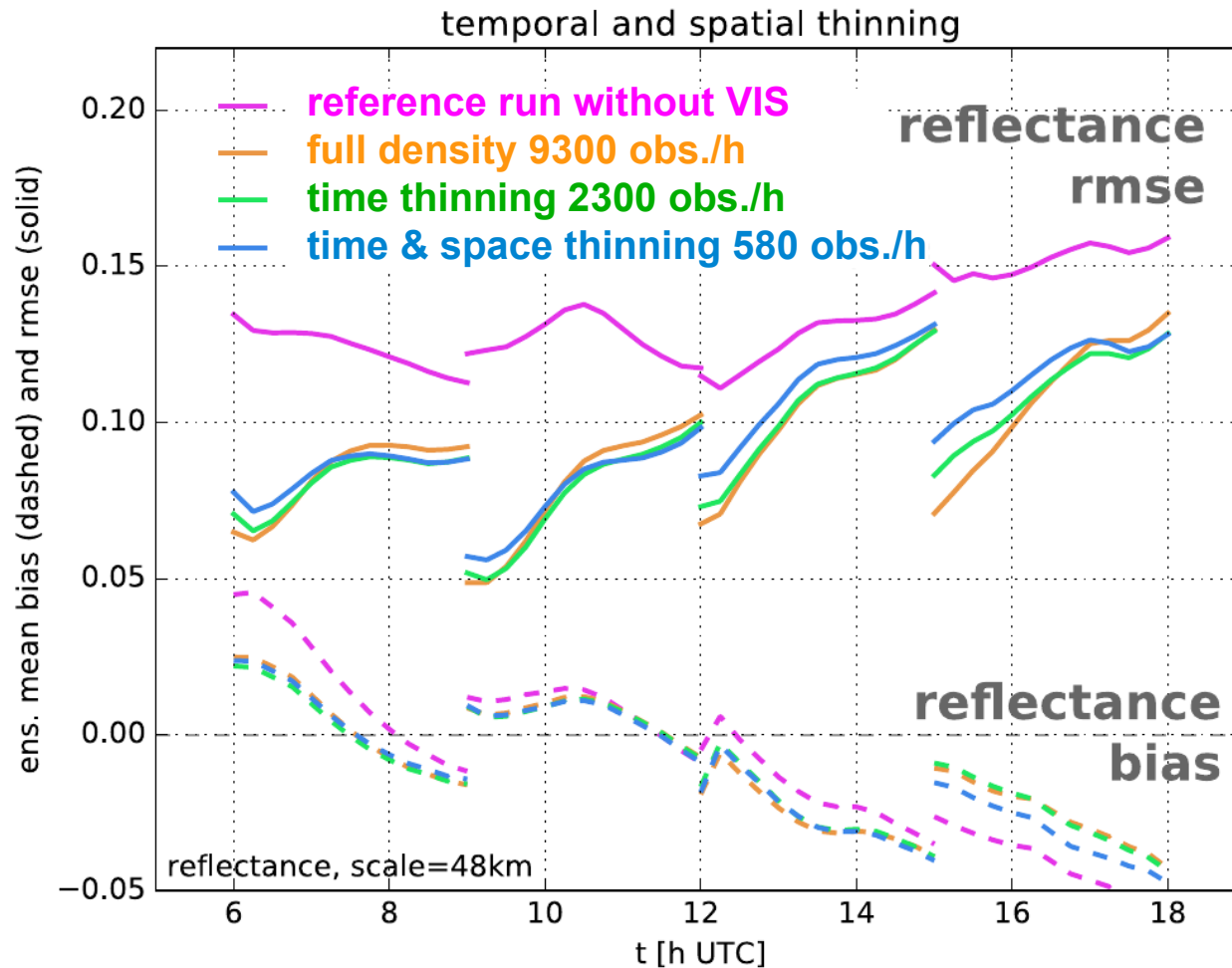
only conv. obs.

P(PRECIP>1mm/h)

conv. + 0.6mu

There are also examples for the suppression of “false alarm” clouds with precipitation...

Reflectance error evolution for different assimilation settings



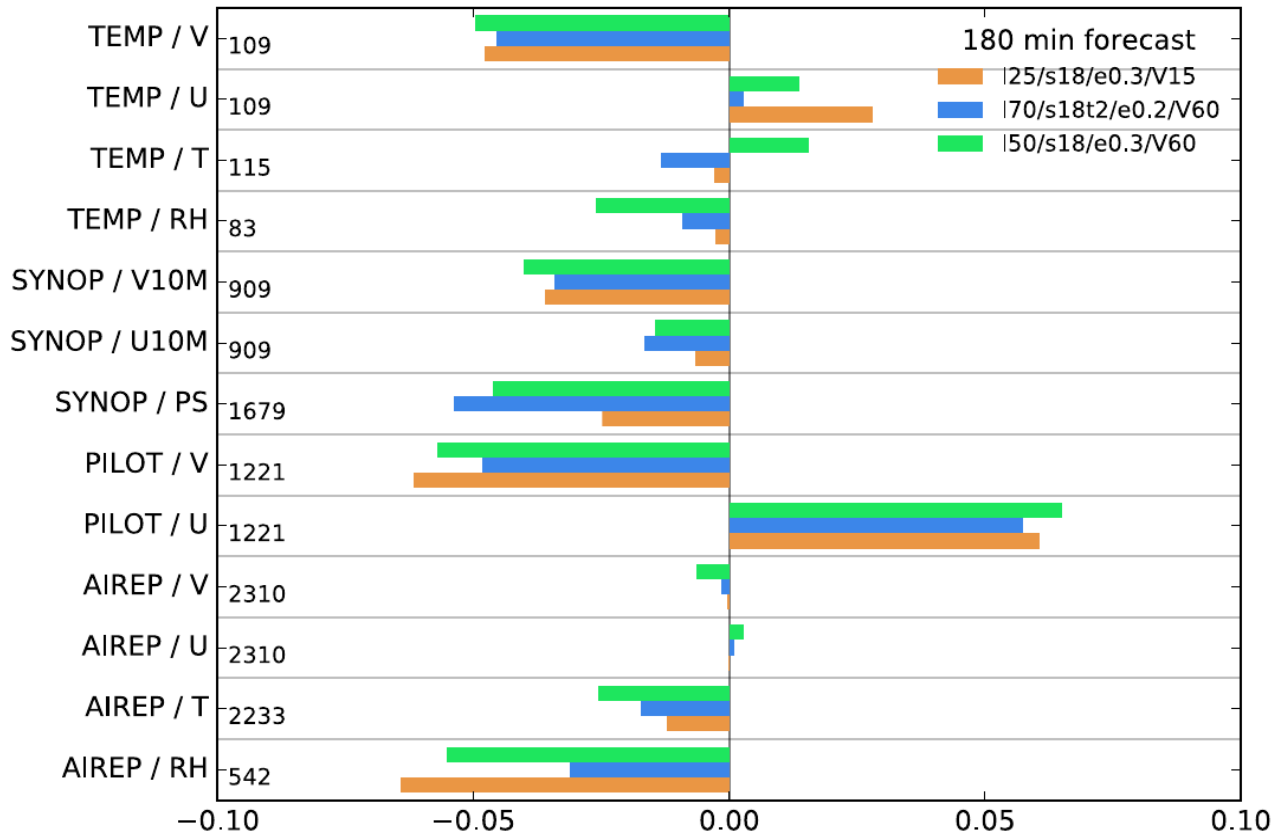
RMSE is smaller than in **reference run** for all settings even after >3 hours. Bias evolution: some clouds dissolve

Full obs. density: (~9300 obs./hour), obs. error 0.3 is better than 0.2 (corr. err.?)

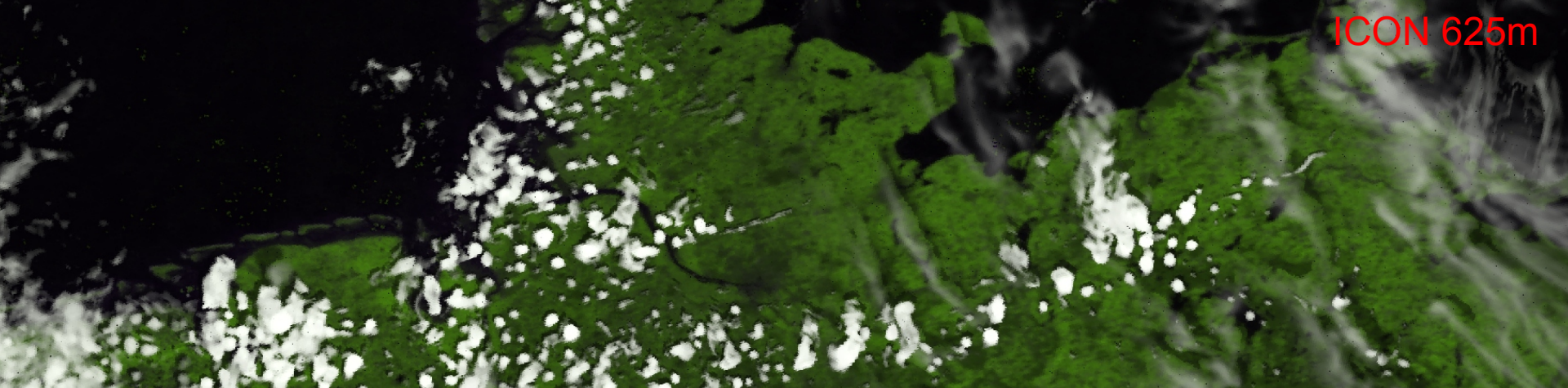
Temporal thinning improves 3h fcsts

Temporal & spatial thinning: similar 3h fcst results

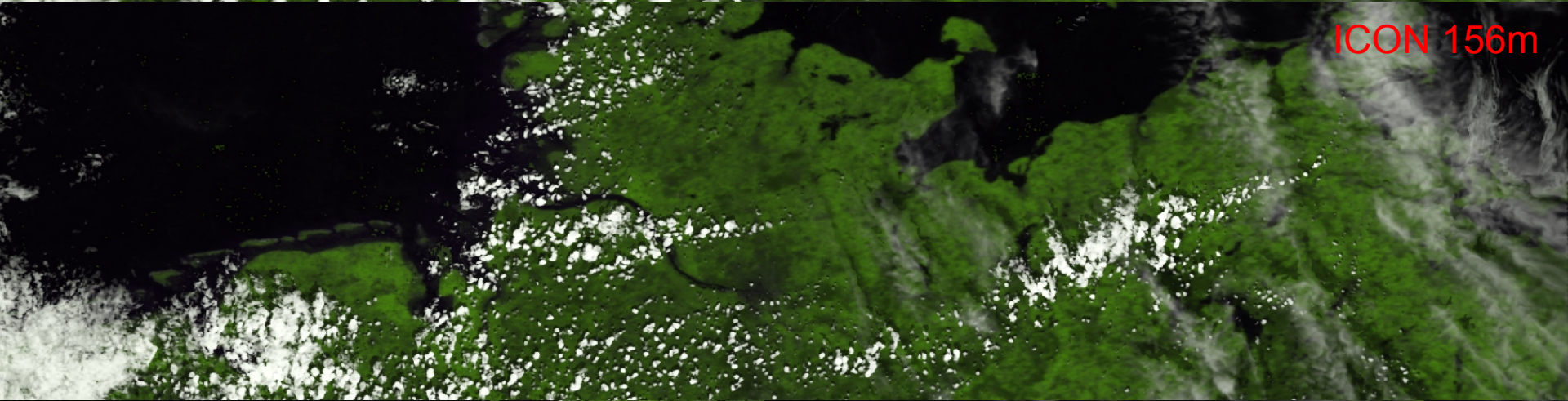
Impact on conventional observations



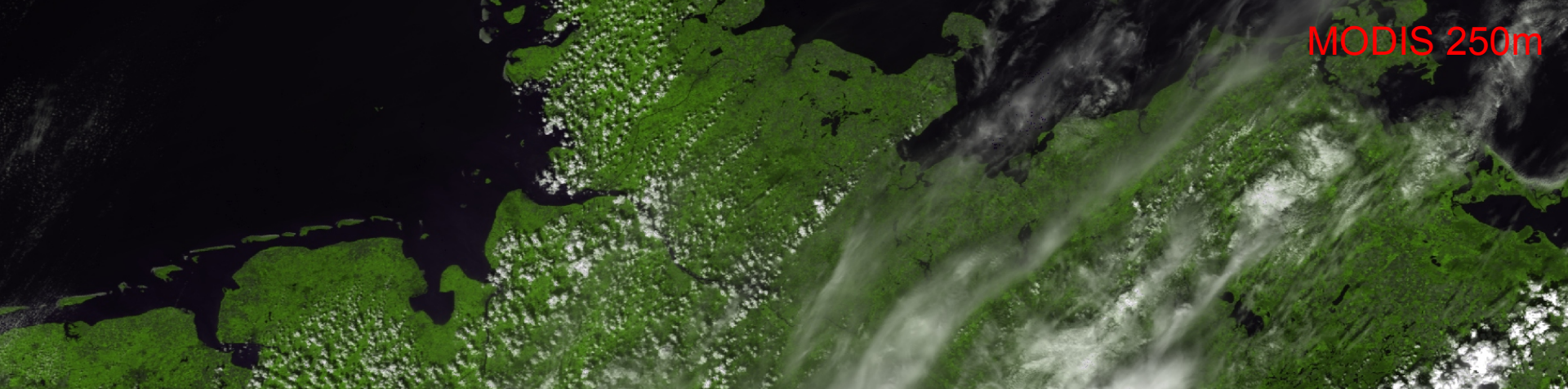
Relative change in RMSE of 3h forecasts caused by VIS assimilation: Mostly beneficial. But this is for only one day... Longer period is under investigation at DWD (Lilo Bach).



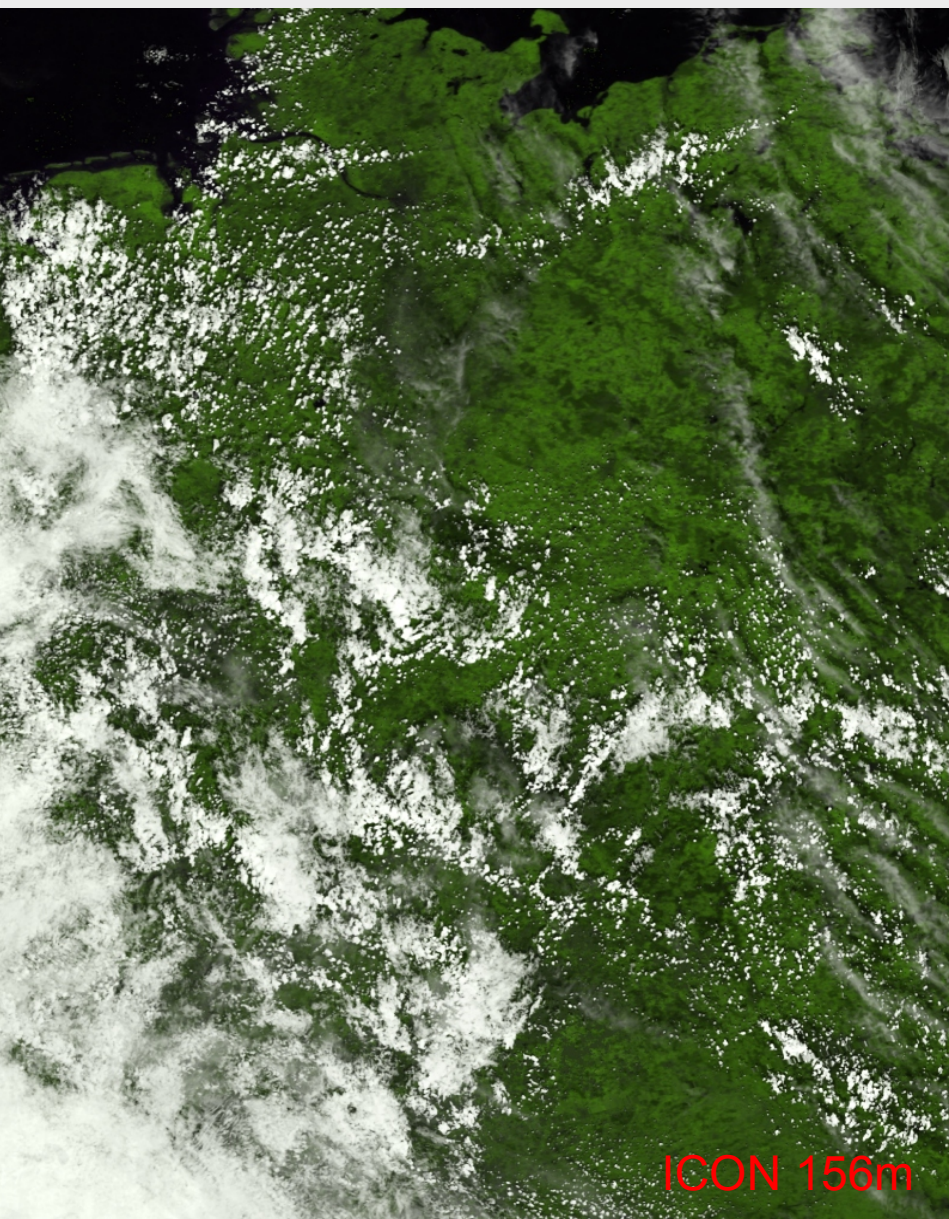
ICON 625m



ICON 156m



MODIS 250m



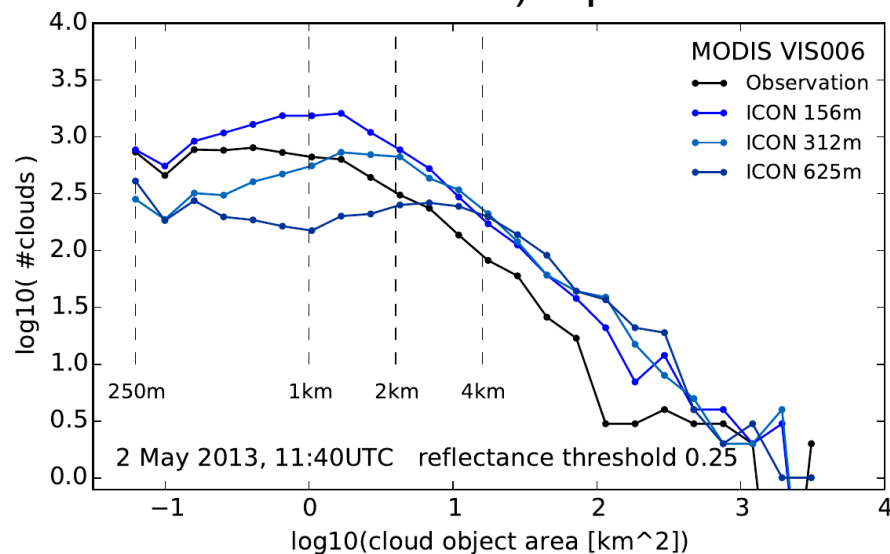
Model evaluation

HD(CP)² : ICON runs with 156m, 312m and 625m resolution for Germany.

Comparison with MODIS (250m)

Paralellized (MPI+OpenMP) offline operator based on MFASIS (still without cloud top inclination 3D correction)

Cloud size distribution: power law (down to effective model res.) reproduced



Summary

- MFASIS: fast method for simulating solar channels (now in RTTOV)
- Cloud top inclination parameterization reduces the systematic error
- Cloud overlap: Tilted columns matter, reflectance spread is small
- Ensemble data assimilation: reflectances & precipitation are improved
- Useful tool for high resolution model evaluation

Next steps: Longer assimilation periods, optimization of assimilation settings, MFASIS for aerosols, more channels, more 3D effects...

Publications:

- Scheck, Frerebeau, Buras-Schnell, Mayer (2016): *A fast radiative transfer method for the simulation of visible satellite imagery*, Journal of Quantitative Spectroscopy and Radiative Transfer, 175, p. 54-67.
- Scheck, Hocking, Saunders (2016): *A comparison of MFASIS and RTTOV-DOM*, NWP-SAF visiting scientist report, http://www.nwpsaf.eu/vs_reports/nwpsaf-mo-vs-054.pdf
- Heinze et al. (2017): *Large-eddy simulations over Germany using ICON: a comprehensive evaluation*, QJRMS, Vol. 143, Issue 702, p. 69-100
- Scheck, Weissmann, Mayer (2018): *Efficient methods to account for cloud top inclination and cloud overlap in synthetic visible satellite images*, JTECH, Vol. 35, Issue: 3, p. 665-685

Results for June 2016 (0.6 μ m SEVIRI images for 3h-COSMO-DE fcsts)

It is essential to take cloud overlap into account, setting all clouds fractions to 1 or using only grid scale clouds causes large errors.

Differences related to different assumptions or implementations are much smaller.

Good agreement with observations (no tuning!)

Cloud fraction 1

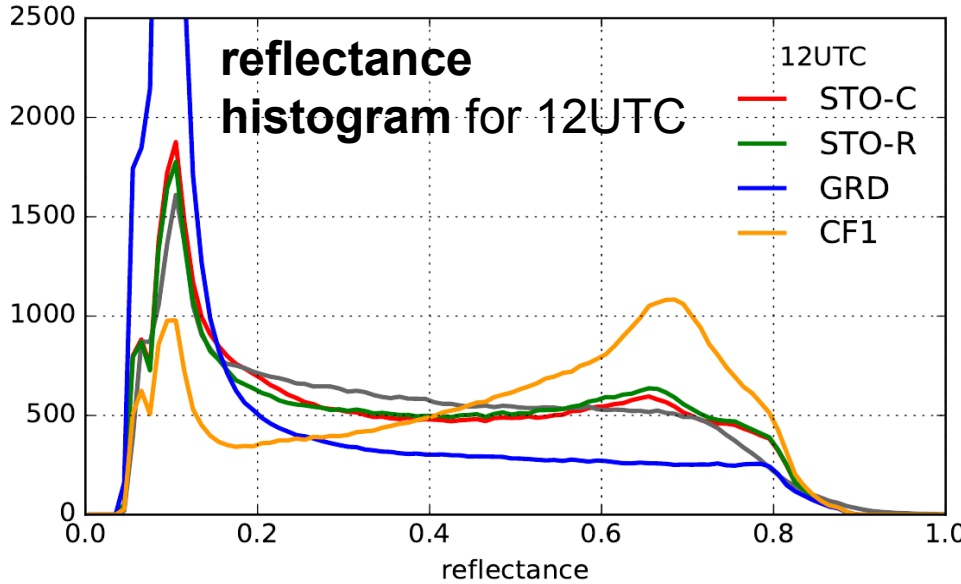
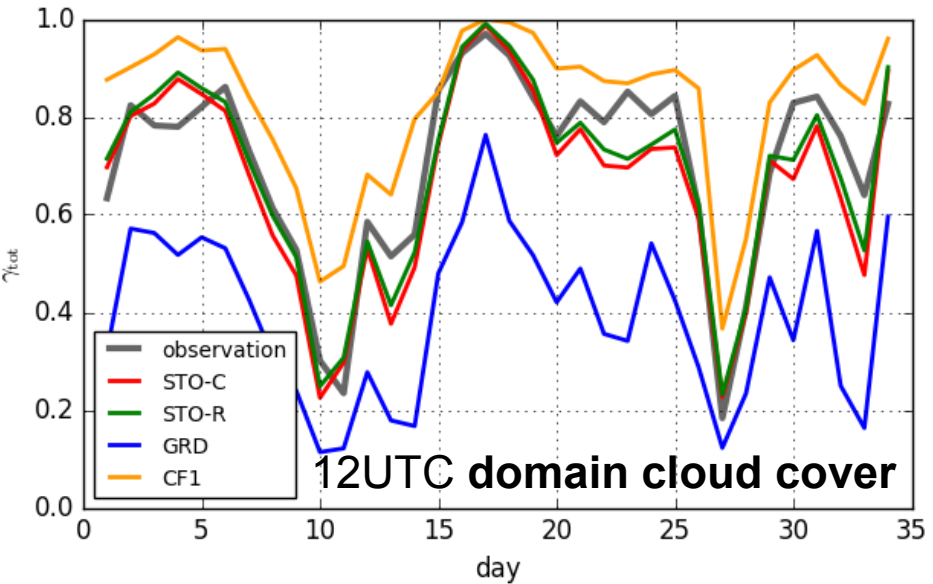
SEVIRI observation

random overlap

random-maximum overlap

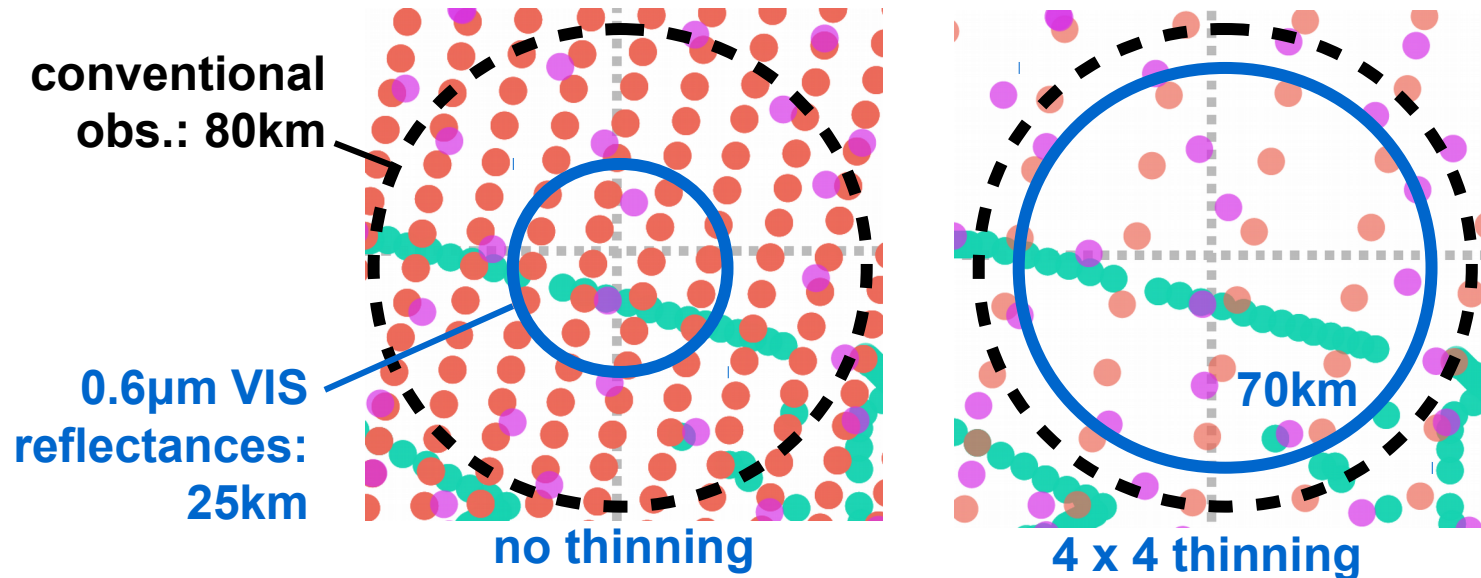
(2D stochastic continuous clouds)

grid scale clouds only



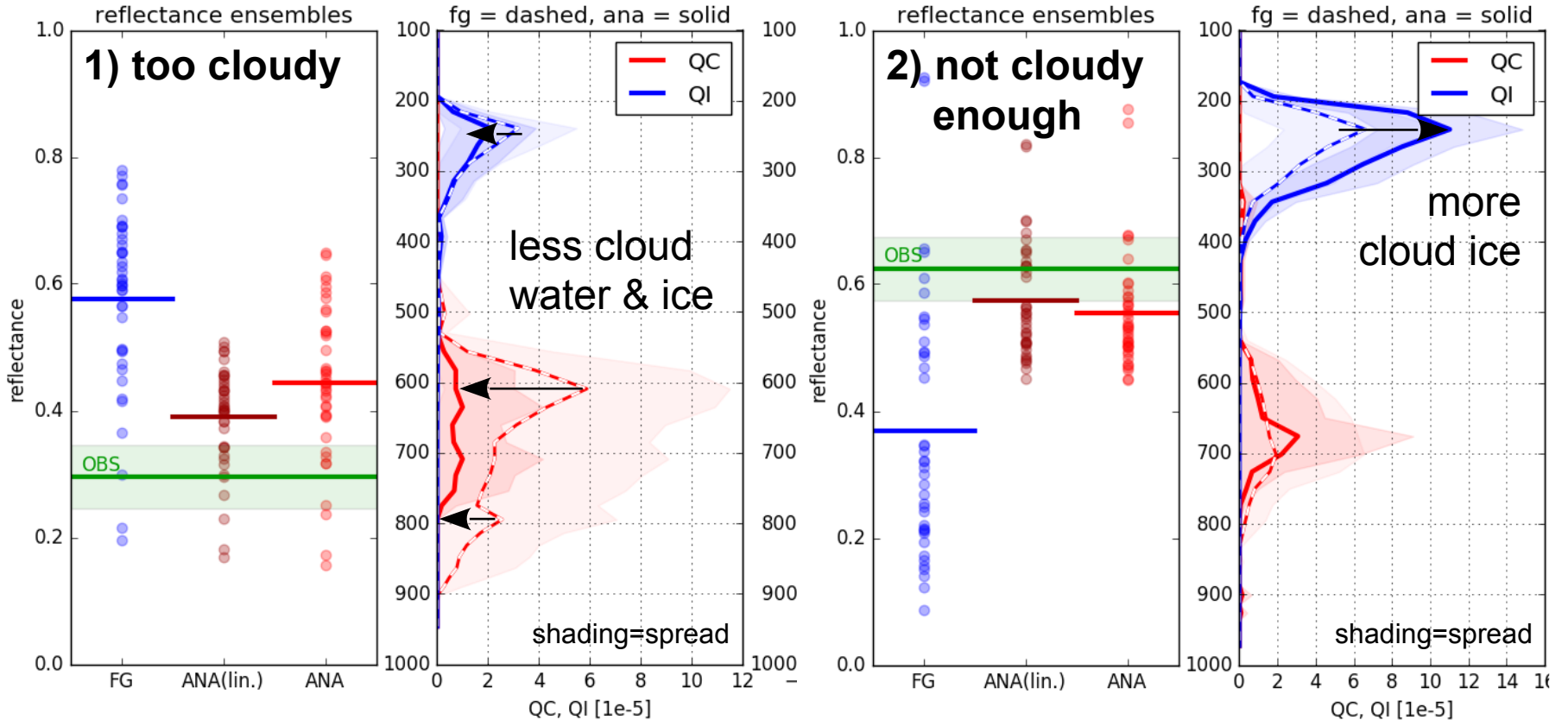
Superobbing, Thinning and Localization

- **Superobbing:** 3 x 6 pixels \rightarrow 18 x 18 km² in model space, $O(\text{eff. model resolution})$
Reflectance obs. every 15min \rightarrow 9255 reflectance superobs. per hour ($>$ conv. obs.)
- **Thinning,** e.g. factors 4 in space & time \rightarrow 581 superobs. per hour ($<$ conv. obs.)



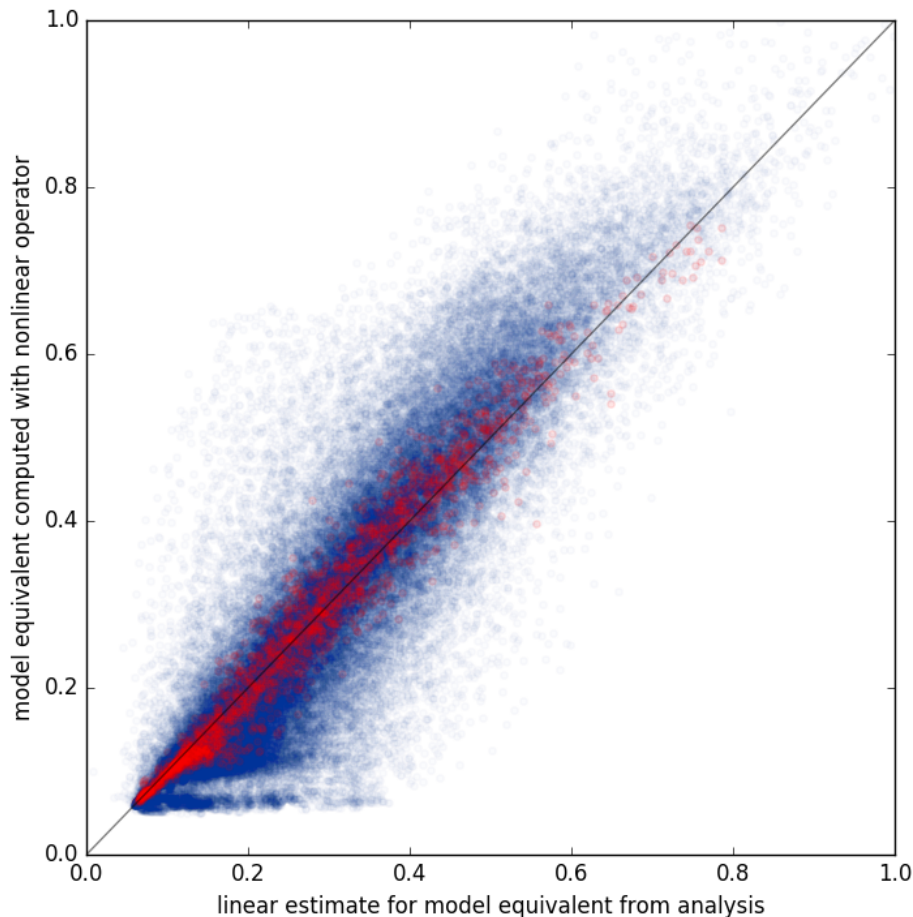
- **Different localizations** (to avoid that VIS overwhelms conv. or vice versa)
 - Aim for both conv. and VIS: **#obs. / grid point $\sim O(\text{ensemble size})$**
 - Reflectances: **No vertical localization**

Single observation experiments



- Model equiv. computed with **nonlinear** operator differ from LETKF estimate
- **Ambiguity** of VIS: LWC, IWC, RH are modified → resolve using other channels?

Nonlinearity of the operator



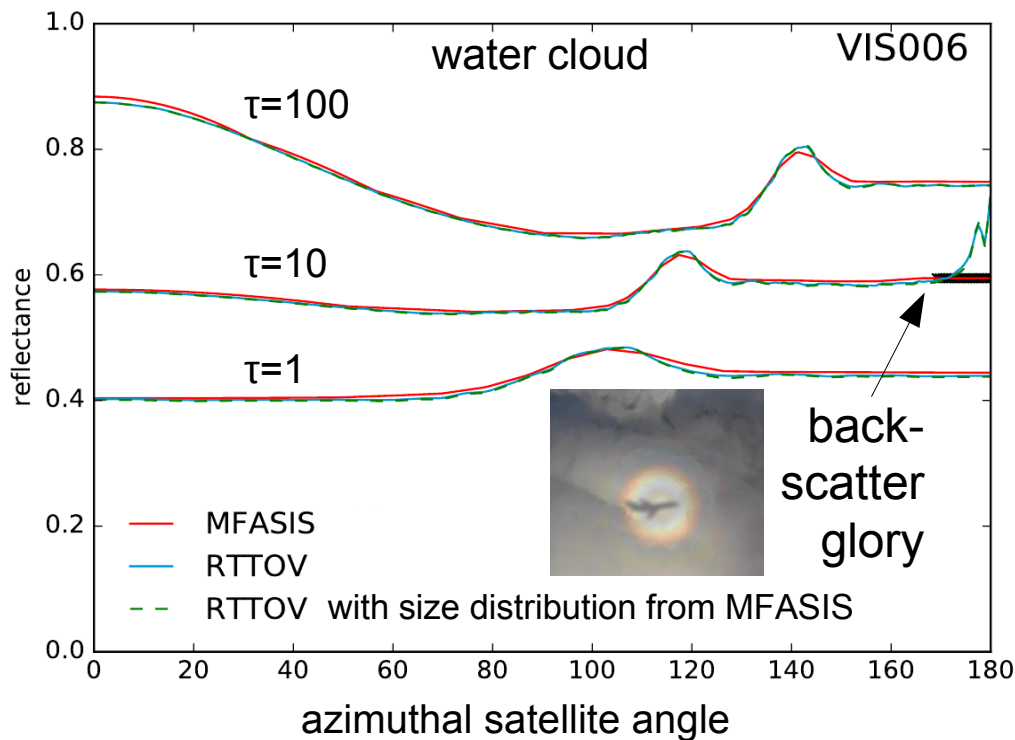
Comparison of linear estimate for analysis model equivalents from LETKF and actual model equivalents obtained by applying nonlinear operator to analysis (incl. inflation, saturation adjustment):
Significant differences for individual (super-)observations (blue), less impact on ensemble mean (red).

Reduces effectiveness of LETKF for large increments
→ avoid long assimilation intervals, assume larger observation errors?
Outer-loop-like strategies?

Comparison with RTTOV-DOM

(with J. Hocking, R. Saunders)

RTTOV-DOM: Implementation of discrete ordinate method by MetOffice / NWP-SAF



- **Reflectances for clouds agree well!**
- **Backscatter glory:** reduced accuracy, depends on unknown width of size distribution
- Clear sky contributions problems:
 - In MFASIS only a constant water vapour profile is included (affects $0.8\mu\text{m}$ channel)
 - linear correction developed
 - RTTOV-DOM: no multiple cloud - clear-sky scattering processes
 - negative bias for dense clouds

MFASIS has been included in RTTOV 12.2 by DWD + MetOffice

See http://www.nwpsaf.eu/vs_reports/nwpsaf-mo-vs-054.pdf

Performance

method	LUT size	time/pixel
DISORT (128 streams)	–	4.9s
DISORT (16 streams)	–	2.3×10^{-2} s
MFASIS ($N_k = N_l = 4$)	36MB	3.3×10^{-6} s
MFASIS ($N_k = N_l = 3$)	21MB	2.5×10^{-6} s
MFASIS ($N_k = N_l = 2$)	9MB	1.8×10^{-6} s

(on Xeon E5-2650 with 20MB level 3 cache)

Scattering angle randomly chosen in $[130^\circ, 140^\circ]$,
all other parameters chosen completely randomly

Scattering angle completely randomly: Only
 $N_k=N_l=4$ (LUT exceeds cache size) is 20% slower.

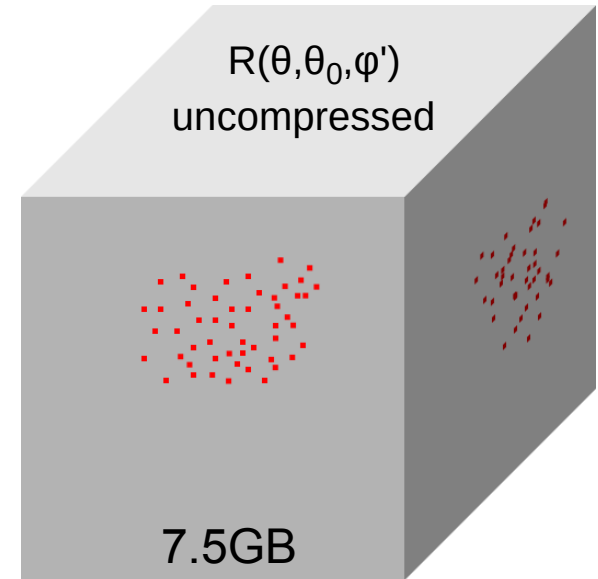
Part of the table required for one SEVIRI image

fits into cache → high performance

→ If required MFASIS LUT can be extended without degrading performance

Uncompressed LUT for $R(\theta, \theta_0, \varphi')$: 7.5GB, limited α range does not help

→ cache misses in almost every pixel → slow!



cache
20MB



~2MB

$R(\theta, \theta_0, \alpha)$,
compressed

LUT compression in MFASIS

Excluded : large θ, θ_0 , very small and large α

$R(\theta, \theta_0, \alpha)$: smooth function for $\alpha = \text{const}$, well approximated by 2D Fourier series

Not all angle combinations are valid:
 $|\theta - \theta_0| \leq \pi - \alpha \leq \theta + \theta_0$

Fit function (symmetric in θ_{\pm}):

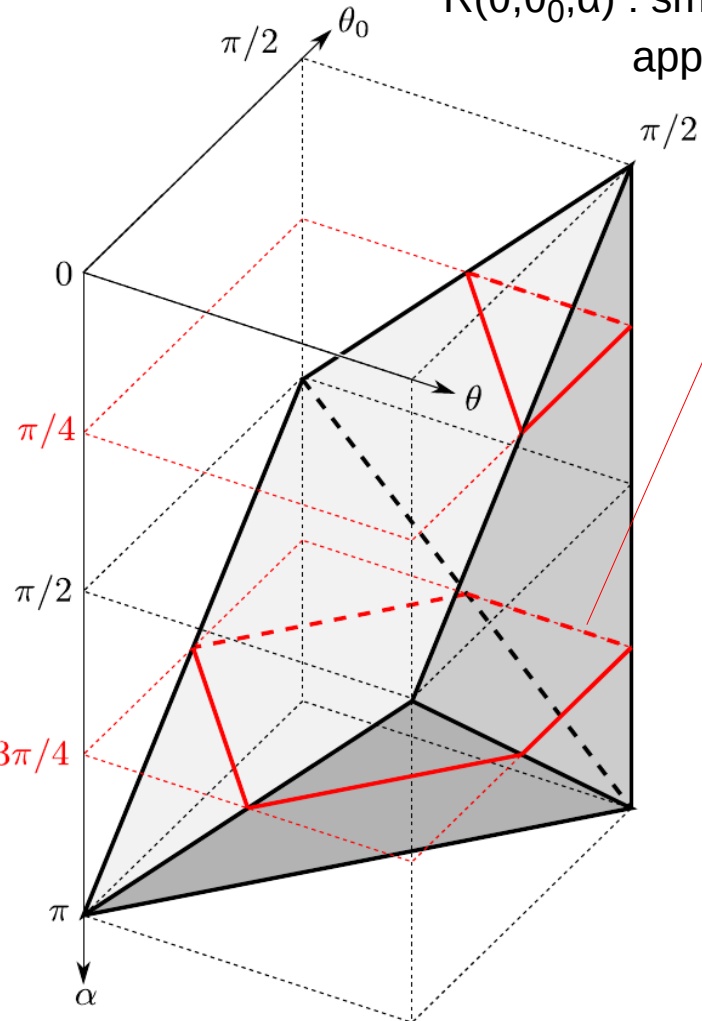
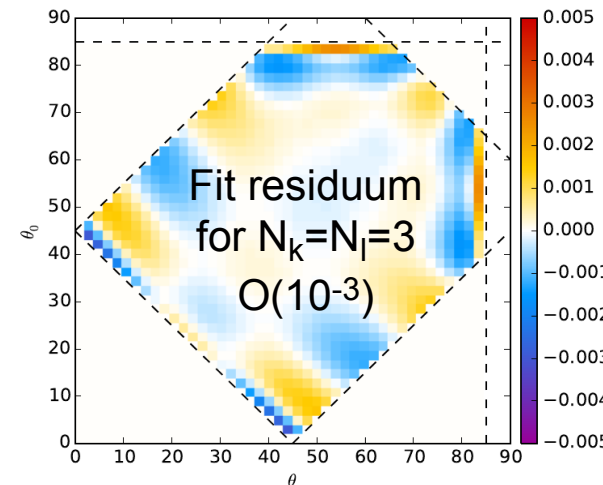
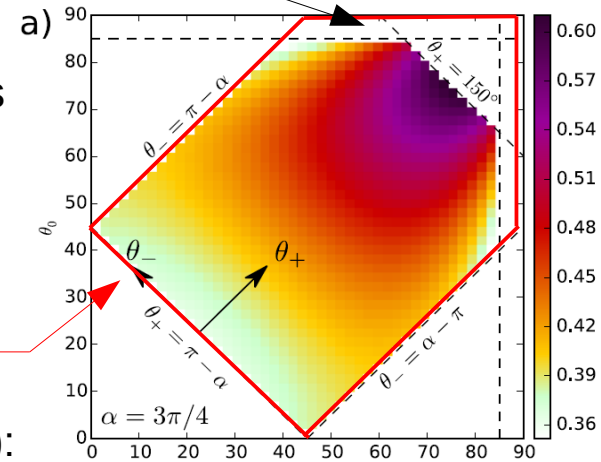
$$R(\theta_+, \theta_-) = \sum_{k=0}^{N_k-1} \sum_{l=0}^{N_l-1} \left[C_{k,l} \cos(k\theta_+) + S_{k,l} \sin((k+1)\theta_+) \right] \cos(l\theta_-)$$

$$\theta_+ = \theta + \theta_0$$

$$\theta_- = \theta - \theta_0$$

Coefficients C_{kl}, S_{kl} :
 obtained by least squares
 fit to DISORT results

$N_k, N_l = 3 \rightarrow 18$ coefficients
 Compression by factor ~ 100
 Does not limit accuracy!



Parameter values in the LUT

C_{kl} , S_{kl} stored in LUTs with dims. α , τ_w , r_w , τ_i , r_i , A

Parameter values are chosen such that linear interpolation error for reflectance < 0.005

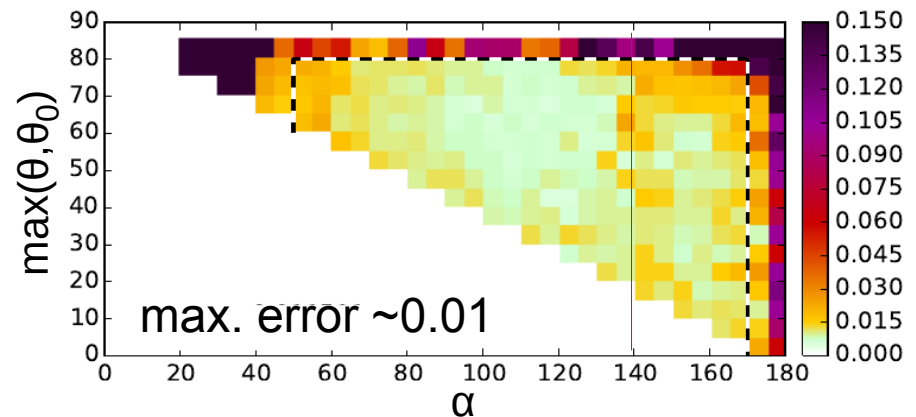
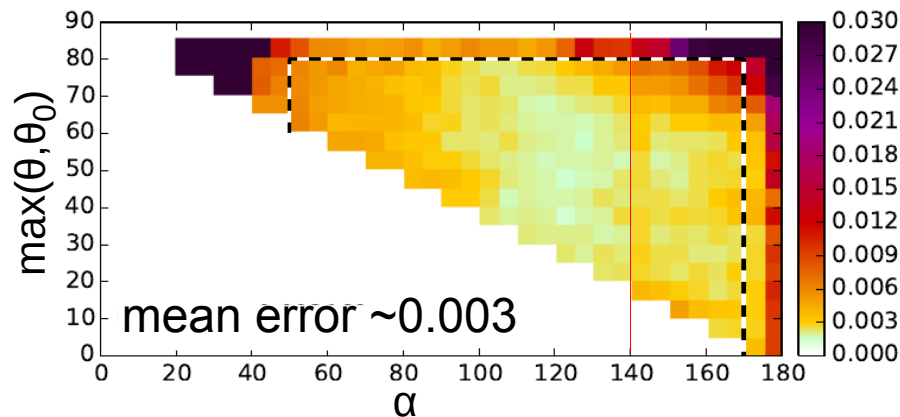
Adaptive α -grid: high resolution (2°) is required only around **cloud bow** \rightarrow LUT factor 3 smaller

parameter	values
A	0.0, 0.5, 1.0
τ_w	0, 0.25, 0.5, 1, 2, 4, 8, 16, 25, 50, 100, 300, 1000
τ_i	0, 0.125, 0.25, 0.5, 1, 2, 4, 8, 16, 25, 50, 100, 300
r_w [μm]	2.5, 5, 10, 25
r_i [μm]	20, 40, 60
α [$^\circ$]	40, 45, 50, 60, 70, 80, 90, 99, 109, 119, 129, 133, 135, 137, 139, 141, 143, 145, 147, 149, 153, 159, 165, 171

Size: 21MB

Fit and interpolation errors

As a function of max. zenith angle and scattering angle for 3 x 3 Fourier terms:



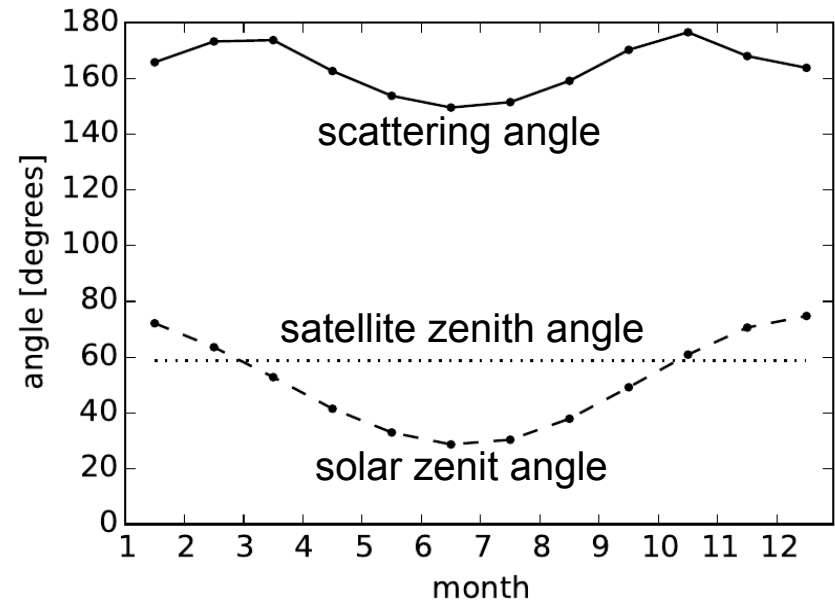
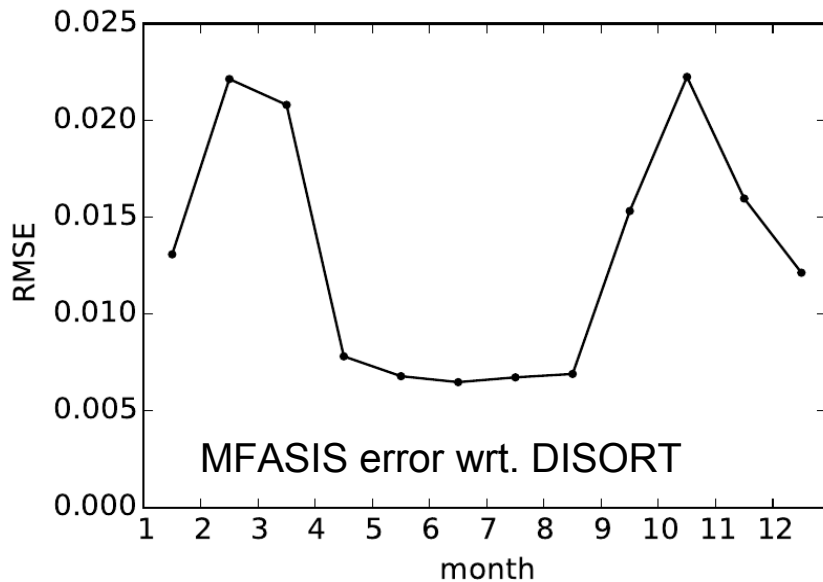
100 randomly chosen cases per $5^\circ \times 5^\circ$ bin

Fit residuum \ll interpolation errors for at least 3 x 3 Fourier terms

Compression does not cause significant error.

Backscattering glory

Atmospheric state from June 15, 2012, 12UTC. Sun angles from other months.



Scattering angles larger than 175° in October / March → Backscattering glory
 → from a geostationary point of view the glory is not a rare event!
 Not included in the LUT → errors several times larger
 Glory depends on width of droplet radius distribution → no input data available
 Assimilation with higher assumed observation error may still be useful.

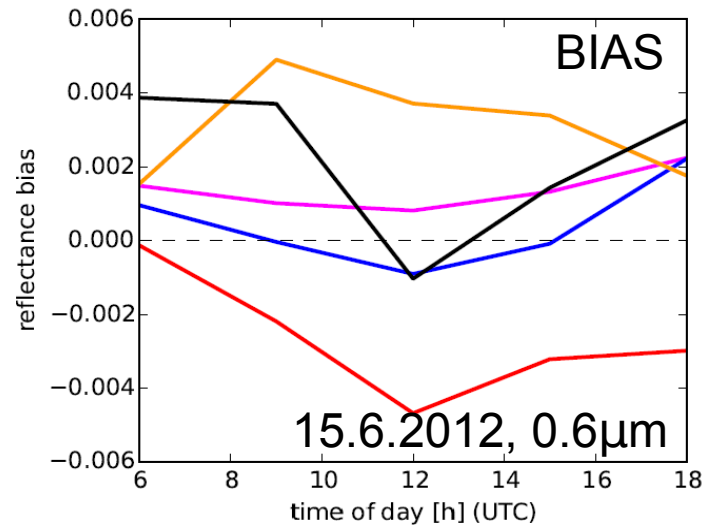
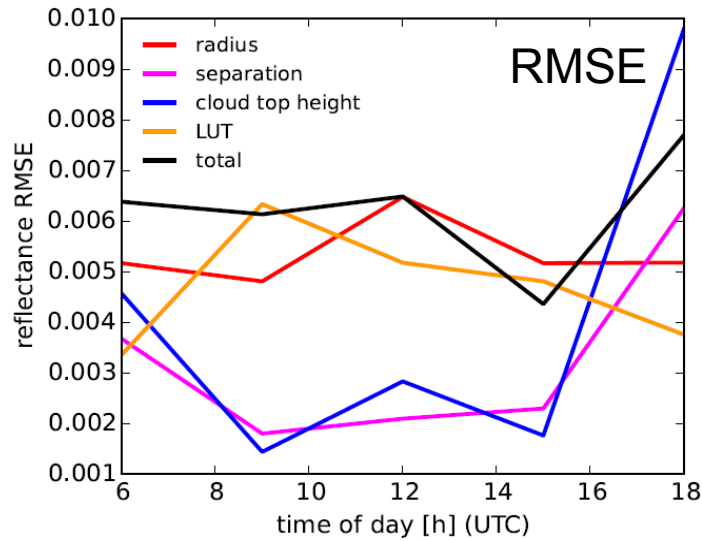
Error decomposition

What is the contribution of the various simplifications to the total error?

one effective radius instead of full profile separation of cloud water and ice fixed cloud top heights fit residuum interpolation error

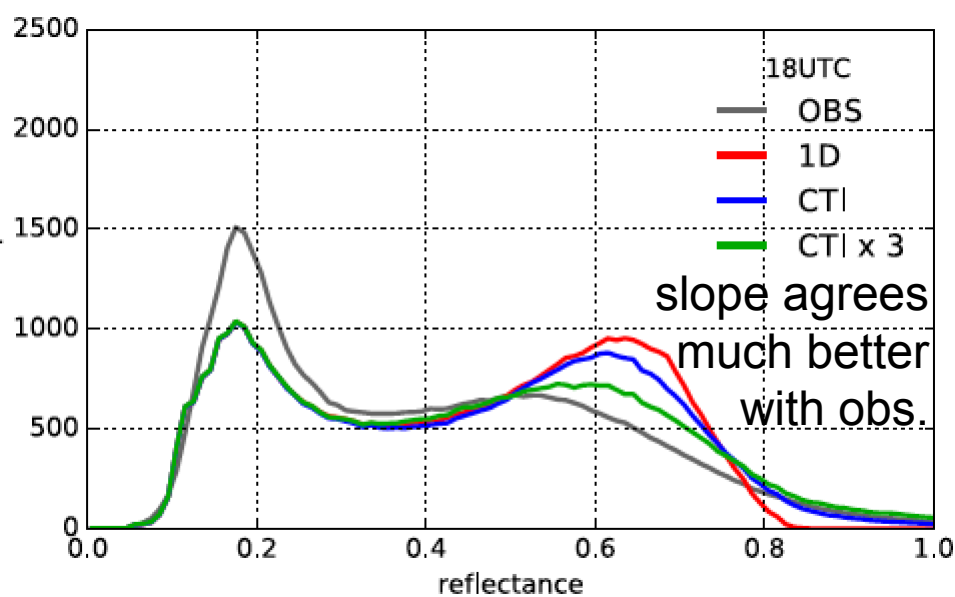
$$R_{\text{DISORT}} - R_{\text{MFASIS}} = \Delta R_{\text{tot}} = \Delta R_{\text{rad}} + \Delta R_{\text{sep}} + \Delta R_{\text{cth}} + \Delta R_{\text{fit}} + \Delta R_{\text{int}}$$

ΔR_{lut}



ΔR_{rad} and ΔR_{int} are the most important and compensate each other partially.
Higher accuracy (e.g. for 1.6μm) requires better way to compute effective radius.

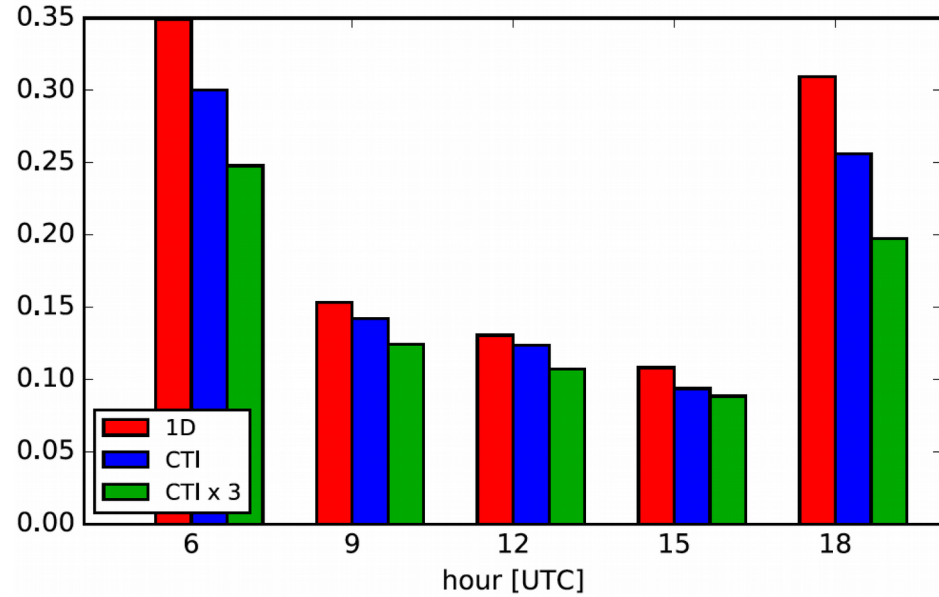
Cloud top inclination correction



0.6 μ reflectance histograms for 18UTC

$$R_T(\theta, \theta_0, \alpha, A, \tau, \theta_i, \phi_i) = R_{\text{full}}(\theta, \theta_0, \alpha, A, \tau) + \delta R_{\text{cti}} \times f(\tau)$$

$$\delta R_{\text{cti}} = R_{\text{cloud}}(\theta', \theta'_0, \alpha, A/\xi_0, \tau\xi) \times \xi_0 - R_{\text{cloud}}(\theta, \theta_0, \alpha, A, \tau).$$

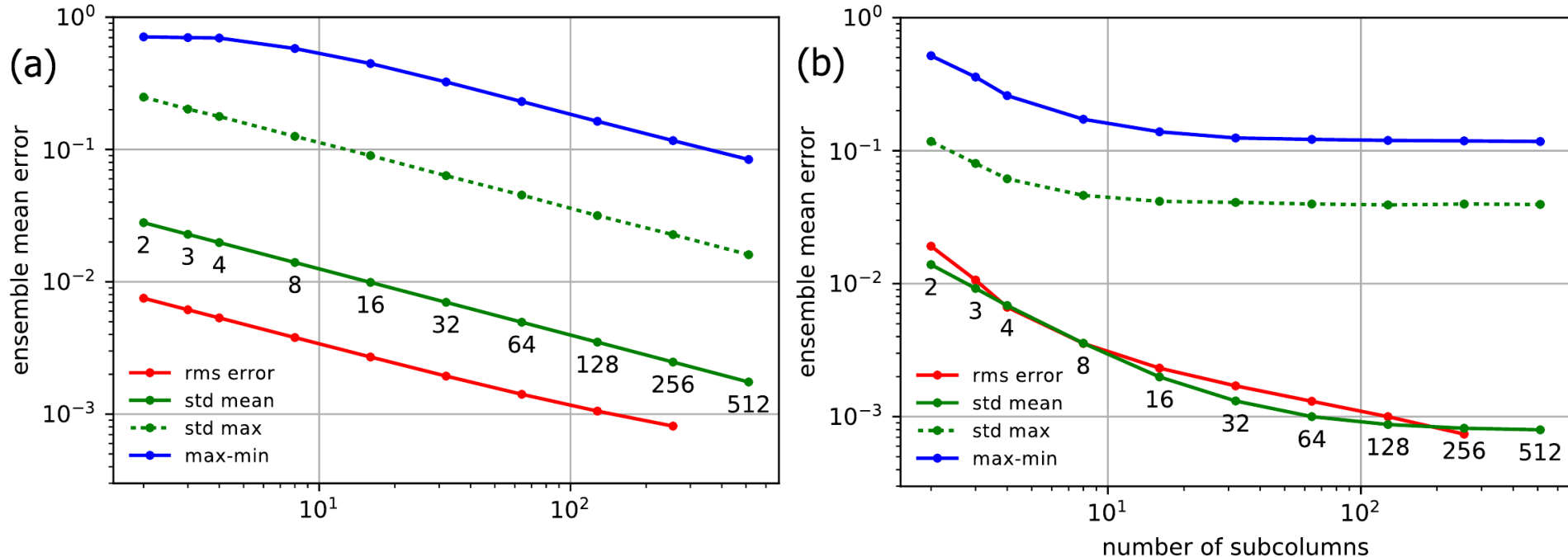


area between obs.& model histogram

$$f(\tau) = \min \left(1, \max \left(0, \frac{\log \tau - \log \tau_{\min}}{\log \tau_{\max} - \log \tau_{\min}} \right) \right)$$

$$\tau_{\min} = 5 \text{ and } \tau_{\max} = 1000.$$

Stochastic overlap schemes: Convergence for smallest / largest cloud approach



(a) Maximum deviation, 99% percentile of the deviation and root mean square deviation in ensemble mean reflectance for the stochastic maximum-random overlap method STO-N with different numbers of streams relative to the 512 stream case computed for the June 2012 test period. Ensembles with 100 members were used. (b) Like (a), but for the STO-C implementation.